Design and Implementation of Single-Image Super-Resolution for Myocardial Scar Image

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ABSTRACT

Super-resolution is the technique of intelligently upscaling images, avoiding artifacts or blurring, and deals with the recovery of a high-resolution image from one or more low-resolution images. Single-image super-resolution is a process of obtaining a high-resolution image from a set of low-resolution observations by signal processing. While super-resolution has been demonstrated to improve image quality in scaled down images in the image domain, its effects on the Fourier-based technique, remains unknown. Super-resolution substantially improved the spatial resolution of the patient LGE images by sharpening the edges of the heart and the scar. This paper aims at investigate the effects of single-image super-resolution on Fourier-based and image based methods of scale-up. In this paper, first generate a training phase of low-resolution image and high-resolution image to obtain dictionary. In the test phase, first generate a patch and then difference of high-resolution image and interpolation image from the low-resolution image. Next simulation of image is obtained by applying convolution method to the dictionary creation image and patch extracted image. Finally super-resolution image is obtained by combining the fused image and difference of high-resolution and interpolated image. Super-resolution reduces image errors and improves the image quality.

Keywords: Super-resolution, single-image, LGE images, Fourier-based, Patch Extraction, Dictionary.

I.INTRODUCTION

Super-resolution is the technique of intelligently upscaling images, avoiding artifacts or blurring, and deals with recovery of a high-resolution image from one or more low-resolution images. Super-resolution techniques are useful in many fields, such as medical imaging, military information acquisition, or consumer electronics. Physically increasing the pixel density of the charge-coupled device (CCD) arrays or the CMOS sensors can be expensive, therefore, recent research has proposed using super-resolution algorithms to increase the resolution of the observed data. The main advantage of this technique is to certain extent to improve the lower resolution of the optical imaging system through integrating high frequency information of low-resolution observations of relative subpixel shift between frames, and the degraded data is restored. The main goal of super-resolution is to produce a detailed, realistic output image and be faithful to the low-resolution input image.

In this paper, the objective is to reduce the image errors in the single-image super-resolution and also to investigate the effects of single-image super-resolution on Fourier-based and image-based methods of scale-up. Super-resolution is a leading role in modern diagnosis of medical image is useful for radiologist or surgeons to detect pathologic or abnormal regions. It is a challenging task to improve the spatial resolution of an imaging system.

In the medical field, single mistake leads to sever problems. So clinicians prefers good image quality image and enhanced image for diagnosis. Conventional techniques using high-resolution ex vivo MRI demonstrated a critical link between complex scar geometry and electrical circuits of ventricular arrhythmia. However, the spatial resolution of clinical cardiac MRI is not sufficiently high to allow reconstruction of the complex scar geometry. In order to allow reconstruction of the complex scar geometry and to increase the image quality single-image super-resolution Fourier-based technique is used.

II. RELATED WORK AND CONTRIBUTIONS

Xiaodong Li et al. [1] introduces Super-Resolution Mapping (SRM) method. SRM is a method for mapping land cover classes with a finer spatial resolution compared to input coarse resolution image. This method will reduce some of the mixed pixel problem of coarse spatial resolution images to a certain extent. A Spatial-Temporal SRM based on a Markov Random Field, called STSRM_SRM has been proposed. The proposed algorithm uses the input as a current coarse spatial resolution Moderate Resolution Imaging Spectrodiometer image and a previous medium spatial resolution Landsat Thematic Mapper image as input. This model helps the spatial smoothing of land cover classes for spatially neighboring subpixels and keeps temporal links between temporally neighboring subpixels in bitemporal images. A significant number of errors including forests that are detected as non-forest patches and non-forests detected as forest patches are observed for SAM. The main factor that caused this error is the coarse spatial resolution of the MODIS image, which reduces the hard classification accuracy of the mixed pixels. By contrast, the errors are reduced in the super-resolution maps.

Jaehwan Jeon et al. [2] proposed a novel single-image super-resolution method is developed using variable sampling positions. This method calculates a Sampling Position Correction Vector (SPCV) from the regularly sampled data based on the local gradient of the image. In pursuit of preserving edge and removing unnatural artifacts in the super-resolution process non-uniformly sampled data obtained by the SPCV is upscaled using the Steering Kernel Resgression Algorithm.

The proposed SR algorithm uses kernel regression method to the restores clear, sharp profile of edge without the reversed gradient or halo effect by modifying the sampling position as well as directionally adaptive interpolation. This reconstruction method is simple and fast, so it is suitable for wide range of imaging devices such as digital cameras, digital TVs and consumer mobile phone cameras. This edge enhancement approach is able to restore edges as sharp as the original edges and therefore to provide better visual quality in the restored high-resolution image. To reconstruct the HR image using irregularly sampling data, the Steering Kernel Regression (SKR) algorithm is used.

Anustup Choudhury et al. [3] present a Face Super-Resolution technique that is based on enhancement of semantic facial components like eyes, eyebrows, nose and mouth. In Face SR approach first step is to prepare a database of training face images. Next step is to align every image in the training database, to estimate the optimal transformation parameters pertaining to rotation, scaling and translation. Next step is to find best matching component from the aligned components. After determining the best matching aligned component, retrieve the gradient information of that component.

Jin Chen et al. [4] presented a Bayesian-based Super-resolution algorithm that uses approximation of symmetric alpha stable (SαS) Markov Random Fields as prior. The approximation SαS prior is used to perform Maximum a Posterior (MAP) estimation for the high-resolution image reconstruction process. As the corresponding energy function is nonconvex, the nonconvexity method is used to solve the MAP estimation problem.

For image restoration, they used a α-stable distribution to better capture the heavy-tailed nature of the data as well as the inter-scale dependencies of wavelet coefficients. This algorithm successfully removes the noise from digital images, which preserves the visual quality of the image very well. The proposed novel method for solving the problem of increasing the spatial resolution of video sequences.

Hiroshi Ashikaga et al. [6] applied an algorithm for single-image super-resolution to myocardial scar imaging to qualitatively asses its effects. The algorithm uses sparse representation and operates by training a pair of low-resolution and high-resolution dictionaries, using neither training images or exploiting a low-resolution version of the image to be handled. While this algorithm of SR has been demonstrated to improve image quality in scaled down images in the image domain, its effect on the Fourier-based image acquisition technique, such as MRI remains unknown. In this proposed system, to compare the effects of SR on different methods of scale-up, three separate data analysis were conducted using the same set of LGE images, separate set of dictionaries were created for each analysis.

1. Zero-padding: A FFT was applied to the high-resolution image to compute the high-resolution k-space. The low-resolution k-space was simulated by extracting the central, low-frequency components of the high-resolution k-space. The low-resolution image was obtained as an FFT of the low-resolution k-space. The interpolation image was obtained by padding zeros around the low-resolution k-space to restore the original size, and by applying inverse FFT to the zero-padded k-space.
2. Bicubic 1: This analysis was conducted to compare the effects of SR between zero-padding and bicubic interpolation. The low-resolution image was simulated as in the zero-padding group. The interpolation image was created by applying bicubic interpolation to low-resolution image.
3. Bicubic2: This analysis was conducted to serve as a positive control of the SR technique. The low-resolution image was created by spatially averaging the high-resolution image. The interpolation image was created by applying bicubic interpolation to the low-resolution image.

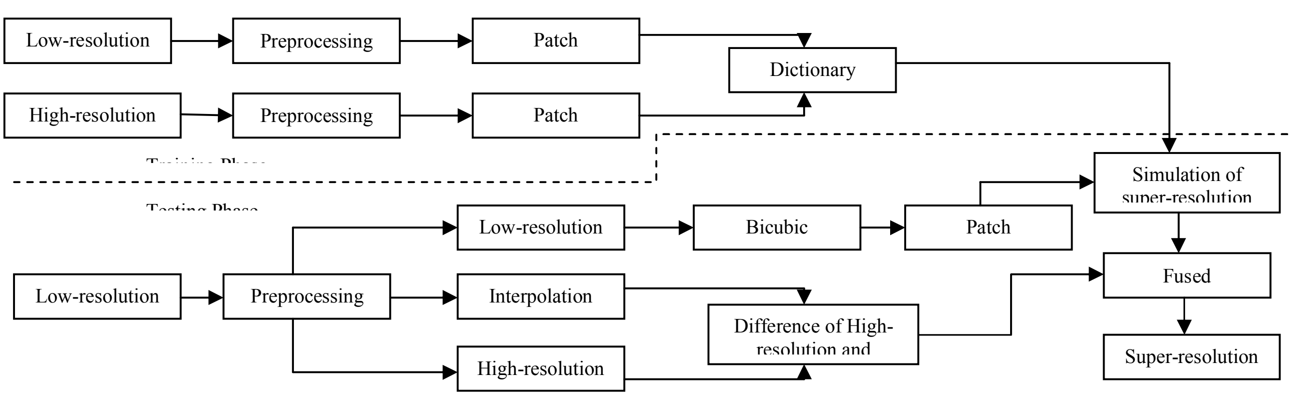


Fig 3.1: Block diagram of the proposed system

III. PROPOSED SYSTEM

The block diagram for the proposed system helps in reducing the image error and improves the image quality and also to investigate the effects of spatial resolution. Block diagram for proposed system is shown in the fig 3.1.

Taking input as myocardial scar image from data base and preprocessing the input image. In the training phase, the dictionary is created by taking input image as low-resolution image and high-resolution image. In the test phase, first patch extraction is done by taking low-resolution image as input image and difference of high-resolution image and interpolated image is obtained by taking low-resolution image as input image. The simulation of image is done by applying convolution method to the dictionary image and patch extracted image. Then combine the fused image difference of high-resolution and interpolation image to obtain super-resolution. Explanation of each block is explained below.

A. Low-resolution image: The pixel density within an image is small, so it offers less details.

B. High-resolution image: The pixel density within an image is large, so it offers more details.

Apply FFT to both the low-resolution image and high-resolution image to obtain a good image quality. FFT is given as,

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi k \frac{n}{N}} \qquad k=0,.................,N-1 \quad (1)$$

C. Interpolation: Interpolation is the process of using known data to estimate values at unknown locations. Interpolation method will select the new pixel from the surrounding pixels. Mainly there are two types of interpolation algorithms:

1) Adaptive algorithms

i) This algorithm changes depending on what they are interpolating.
ii) It involves lot of calculations.

2) Non adaptive algorithms

i) The algorithm interpolate by fixed pattern for all pixels.
ii) Hence, it has the advantage of easy performance and low calculation cost.

Non adaptive algorithm includes linear interpolation algorithms. Linear interpolation includes nearest neighbor, bilinear, bicubic interpolation. In this paper, bicubic interpolation is used because of drawbacks in adaptive algorithm.

D. Bicubic Interpolation: Bicubic interpolation solves for the value at a new point by analyzing the 16 data points surrounding the interpolation region. It considers the closest 4×4 neighborhood of known pixels for a total of 16 pixels. When these are at various distances from the unknown pixel, closer pixels are taken for the calculation of a higher weighting. Bicubic produces sharper images than the nearest neighbor and bilinear methods, and is perhaps the ideal combination of processing time and output quality. For this reason it is a standard used in many image editing programs, printer drivers and in-camera interpolation.

Suppose the function values f and the derivatives f_x, f_y and f_{xy} are known at the four corners (0,0), (1,0), (0,1) and (1,1) of the unit square. The interpolated surface can then be written as,

$$p(x,y) = \sum_{i=0}^{3} x^i \sum_{j=0}^{3} y^j a_{ij} \qquad (2)$$

As the more adjacent pixels it includes, the more accurate it can become. Hence in this paper interpolation is done by using bicubic interpolation.

E. Patch Extraction: Patch extraction is done by taking the bicubic interpolation image as a input image. Resize the input image and the initialize the patch size to 10. For every patch size, patch is extracted for the whole image and display it in the image.

F. Cubic Spline: Cubic spline is the one of the method of interpolation. Apply analytical interpolation to the low-resolution image i.e., cubic spline.

A k-degree spline curve is a function of piecewise polynomial where

1. each piece is of degree at most k,
2. the curve is k-1 times continuously differentiable.

The most important form of spline curve has degree 3. It is also called as cubic spline. The spline is given as,

$$f_i(x) = a_i + b_i t + c_i t^2 + d_i t^3 \; for \; t \varepsilon [0,1] \qquad (3)$$

where, i=0,.......,n-1. There are three sets of conditions on the coefficients:

1. f(x) must match y_i's at the knots.
2. f'(x) must match at the knots.
3. f''(x) must match at the knots.

Then,

$$f_i'(x) = \frac{1}{\delta}(b_i + 2c_i t + 3d_i t^2) \quad (4)$$

$$f_i''(x) = \frac{1}{\delta^2}(2c_i + 6d_i t) \quad (5)$$

G. Difference of High-resolution and Interpolation image: The difference of high-resolution image and interpolation image is taken and given as,

$$diffImg(x,y) = interImg(x,y) - hiInterImg(x,y) \quad (6)$$

H. Dictionary Creation: In this, compare the values with the dictionary created under training phase. Each and every value will be compared with the obtained value.

I. Simulation of Super-resolution images: Simulation of super-resolution image is obtained by using training phase of dictionary image and test set of patch extracted images. This simulation is done by using convolution method. From this obtain a super-resolution image with loss of information. Convolution is given by,

$$f[x] * g[x] = \sum_{k=-\infty}^{\infty} f[k] \cdot g[x-k] \quad (7)$$

J. Fused: Fused is a combination of simulation of super-resolution image and the difference of high-resolution and interpolation image. In this the lost information of both simulation of super-resolution image and a difference of high-resolution and interpolation image is combined to obtain fused image.

K. Super-resolution image: Apply IFFT to obtain a required super-resolution image**.** IFFT is given by**,**

$$x_n = \frac{1}{N}\sum_{k=0}^{k-1} X_k e^{i2\pi k\frac{n}{N}} \qquad n=0,\dots\dots\dots\dots,N-1 \quad (8)$$

IV. SYSTEM IMPLEMENTATION

The proposed system is implemented in Matlab version R2010a with the help of guide which is shown in Fig.4.1. The detailed description is explained below.

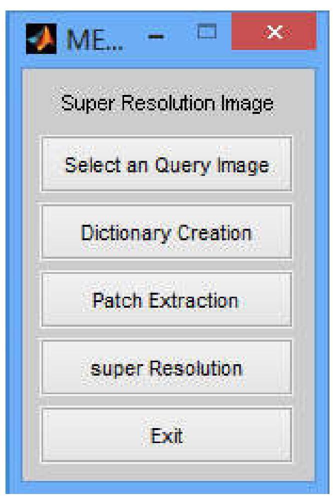


Fig.4.1: GUI for the proposed system

Here the input image, is taken from the data sets of myocardial scar image in training phase and this is selected by using select an query image command. The obtained image is resized by using preprocessing, from this low-resolution image (256 × 256) and high-resolution image (256 × 256) is obtained for this apply FFT then obtain a patch for both the images, patch size will be 8. Then creating the dictionary for both the images, this is done under dictionary creation command.

In the test phase, the low-resolution image is taken as input image and preprocessing that image to (256 × 256) size then apply bicubic interpolation to obtain patch extraction. Apply interpolation to the low-resolution image to obtain interpolation image and apply histogram equalization to the interpolated image to obtain high-resolution image.

From high-resolution image and interpolated image obtain the difference of image and apply FFT to the difference of image this is done under patch extraction command. Simulation of image is obtained by applying convolution method to dictionary image and patch extracted image. Fused image is obtained by taking the average of the difference of image and simulation of image. Apply IFFT to the fused image to obtain the Super-resolution image. The flow chart of the proposed system is shown in fig 4.2.

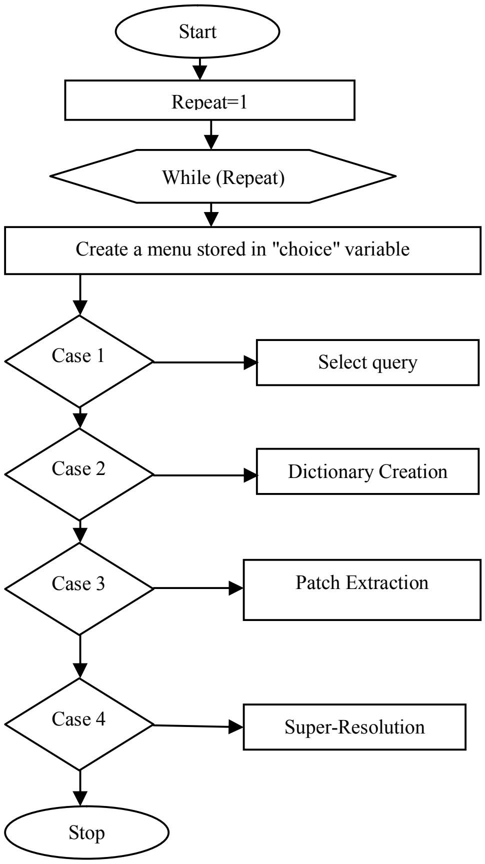
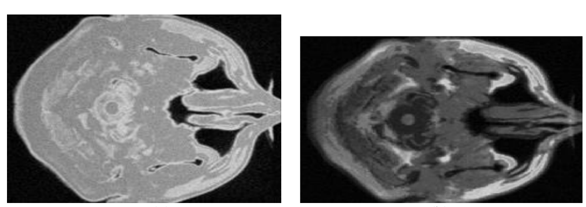


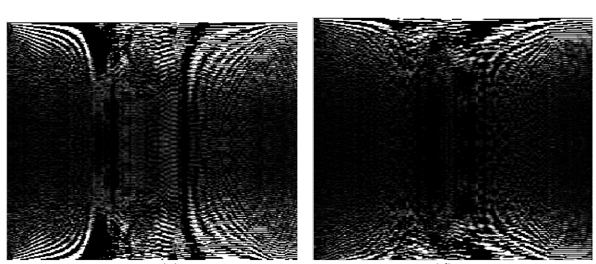
Fig 4.2: Flow chat of the proposed system

V. RESULTS

The experimental results for training phase, test phase, simulation of image, fused image and the Super-resolution image from the input low-resolution image and high-resolution image. The simulation results of super-resolution for myocardial scar image is shown in fig 5.1.



(a) (b)



(c) (d)

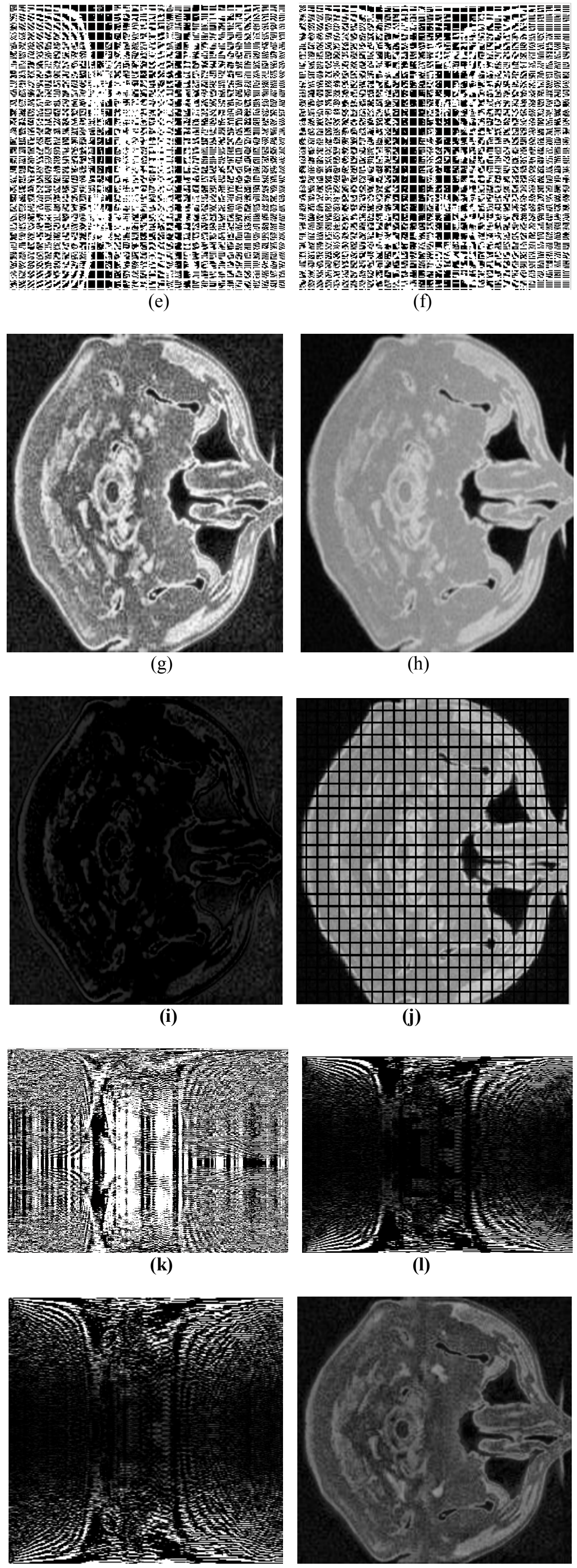


Fig. 5.1: (a) Input Low-resolution image (256 × 256) matrix (b)Input High-resolution image (256 × 256) matrix (c) FFT of low-resolution image (d)) FFT of high-resolution image (e)FFT of low-resolution patch (f) FFT of high-resolution patch (g) Interpolation image (256 × 256) matrix (h)Output High-resolution image (256 × 256) matrix (i)Difference of high-resolution and interpolation image (j) Patch extraction of an image (k)FFT of Difference of high-resolution and interpolation image (l) Simulated image (m)Fused image (n)Super-resolution of an image.

A) Tabulation for PSNR, RMSE and MAE values

SI. No	PSNR(dB)	RMSE	MAE
1	26.727	13.638	59.397
2	26.813	13.605	59.662
3	26.889	13.587	59.522

Table 1: Tabulation for PSNR, RMSE and MAE values

VI. CONCLUSION

In this paper, Single-image super-resolution method has been designed and implemented for both the training phase and test phase to obtain the super-resolution image. The FFT is applied to the input low-resolution image of (256×256) matrix and high-resolution image of (256×256) matrix. The interpolation image of (256×256) matrix is obtained by applying interpolation to the low-resolution image of (256×256) matrix and high-resolution image of (256×256) matrix is obtained by applying histogram equalization to the interpolated image. Patch Extraction is also implemented by taking bicubic interpolation image as input image. In the training phase, the dictionary is created by comparing the values of low-resolution image of (256×256) matrix and high-resolution image of (256×256) matrix. By combining the dictionary creation of image from training phase and patch extraction of test phase to obtain the simulation of super-resolution image. By combining the fused image and difference of image and apply IFFT obtains a super-resolution image. This image can be used to improve image quality of medical images and reduces the image error, which is very useful in diagnosis purposes.

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