Edge-Preserving MRI Super Resolution Using a High Frequency Regularization Technique

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***Abstract-* The resolution of MRI images is limited due to several factors such as imaging hardware or time constraints. However, high MRI image resolution is desired in many medical applications. Traditional Super Resolution (SR) algorithms are generally unable to recover the high frequency (HF) information of MRI images. Recently, spatial adaptive SR algorithms have utilized the combined edge preserving and smoothness constraint methods to improve the quality of the images. Segmenting the image into edge and smooth blocks is a common step which adds to the complexity and execution time of these methods. This paper presents a fast SR technique for MRI images that preserve the edges and improve the visual quality of MRI images without segmenting the images. Experimental results prove the ability of this proposed approach with respect to the traditional SR methods in terms of better visual quality and less execution time.**

***Keyword*: Super resolution, MRI, High frequency regularization**

I. INTRODUCTION

High resolution images reveal more information in acquired MRI images. In many cases, the medical image voxel size is limited by a number of factors such as imaging hardware, time constraints, or patient's comfort. To alleviate these problems, image super resolution (SR) techniques have become a popular approach to estimate a high resolution (HR) image from a low resolution (LR) image [1-2]. Tsai and Huang [3] proposed the first algorithmic technique for SR image reconstruction in 1984. In recent years, SR methods have achieved great success in medical applications [4-5]. However, most of these techniques are based on the acquisition of multiple low resolution (LR) MRI images with sub-pixel shifts that are time-consuming and therefore not adequate for patients and typical clinical settings [6].

Most of the traditional single SR algorithms such as bilinear or Bicubic interpolation focus on overlaying smoothed images to reduce the ringing or jagged artifacts. Interpolation by exploiting the natural image priors will generally produce more favorable results. However, these algorithms destroy the edges which are very informative on medical images.

A successful SR algorithm should reproduce the observed LR image after applying the same generation model to the reconstructed HR image. This is the fundamental reconstruction constraint for SR models that result in a severely ill-posed problem. To remedy this problem, regularization methods are introduced in order to find a stable solution. Most of the regularization based algorithms apply the Tikhonov regularization method [7] for SR reconstruction. It introduces smoothness constraints to suppress the noise in the reconstruction process, while it loses details (edge information) of LR images which are very critical for MRI images. To preserve details and edge information Farsiu et al.[8] introduces the bilateral total variation (BTV) operator as a regularization term measured by L_1 norm. However, BTV is not locally adaptive and fails to consider the partial smoothness of an image. Thus, it has limited capability in SR reconstruction and cannot balance the suppression of noise against the preservation of image details.

In this paper, a novel SR algorithm based on high frequency (HF) regularization is introduced to reconstruct an HR image from a single MRI image in order to improve the visual quality and preserve the edge information. In the initial step, an HR grid is reconstructed using the interpolation values of the LR image. This initial HR image is smooth due to going through the interpolation process. Therefore, an HF layer of a LR image is obtained by subtraction of the down-sampled HR from the LR image. The HF layer is then added to the regularization term to preserve the edges in a back projection step. The rest of this paper is organized as follows. The degradation of digital image is introduced in Section 2. Section 3 describes different steps of the proposed method such as initialization and back projection. The experimental results in section 4 evaluate the model on clinical images to prove the superiority of the proposed model over other traditional SR techniques, and the last section is devoted to concluding and future works remarks.

II. THE DEGRADATION MODEL OF DIGITAL IMAGES

This section explains the model of image degradation process in the acquisition of MRI images. MRI provides intensities for each voxel. The intensity values of an MRI image are proportional to the number of nuclei in each voxel and are affected by the nuclear relaxation times and the pulse sequence used. In the MRI process, there is a natural loss of spatial resolution caused by gradients' intensity, digital imaging filter bandwidth, the number of "read out" points and phase encoding step. In summary, the final MRI image is usually warped as a result of relative distortion $M(\cdot)$. The continuous point spread function $H(x,y)$ blurs the image. Therefore, the observed digitized noisy LR image $Y(i,j)$ is represented by the following degradation model:

$$Y(i,j) = M\big(H(x,y) * X(x,y)\big) \downarrow + \varepsilon(i,j) \quad (1)$$

where $X(x,y)$ is the HR image, $\varepsilon(i,j)$ is the system noise, $*$ is the 2D-convolution, and $\downarrow$ indicates the down-sampling function.

A more common notation used in [8-10] defines observed LR images as following:

$$Y = DHMX + \varepsilon \quad (2)$$

where $D, H, M,$ and ε are the down-sampling, blurring, distortion warp, and noise functions, respectively. In general, the spatial distortion $M(\cdot)$ includes translation, rotation, deformation, and other possible distortions in the MRI process. Following the conventional formulation of super resolution, the HR and LR image matrices are converted to vector form, $X: (rn, rm) \rightarrow (r^2nm, 1)$ and $Y: (n, m) \rightarrow (nm, 1)$, where r is the up-sampling scale factor, n and m represents the horizontal and vertical sizes of the LR image, respectively. To keep the consistency in Eq. (2), the sizes of H and M matrices are (r^2nm, r^2nm) and the size of the down-sampling matrix D is (nm, r^2nm).

III. PROPOSED SR METHOD

The proposed method for obtaining a high quality HR image from an input of LR image consists of three steps. First, an initial HR image (X_0) is constructed by simply using an interpolation scheme from the MRI input image. The second step is focused on obtaining the HF layer of X_0 . The HF layer of LR image represented as E_{LR} is obtained by subtracting the down-sampled X_0 from the original MRI image. The HF layer is then extended to the size of HR image. In the final step, an iterative back projection process is applied in which the HF layer contributes to the HR image reconstruction as a regularization term in order to obtain the final refined HR image. Fig. 1 shows the flowchart of the proposed model.

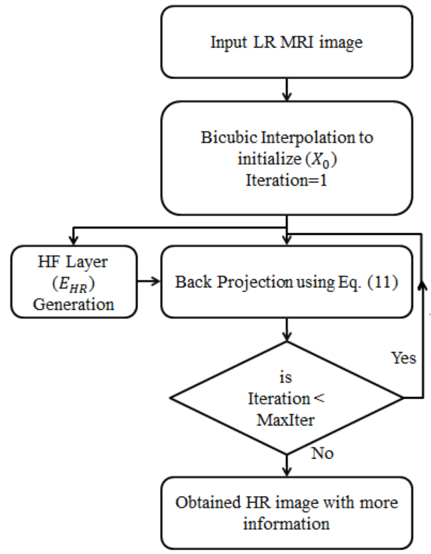

Fig. 1 Block diagram of the proposed method

In summary, the proposed method is expressed as following:

- *Find initial HR image X_0.*
- *Obtain the HF layer of X_0.*
- *Apply iterative back projection using HF regularization.*

A. Construction of the Initial HR image

The initial approximation of the input image is very important for any gradient-descent based optimization technique. For our purpose, any existing interpolation methods can be used to obtain the first approximation. However, Bicubic interpolation is considered to be very effective for SR image reconstruction. The proposed method applies a Bicubic interpolation to resize the input MRI image to the desired HR image size, as shown in Fig. 2. In this way, the initial HR image on a HR grid sampling points is obtained. The actual values of the HR image are obtained directly from the Bicubic reconstruction procedure.

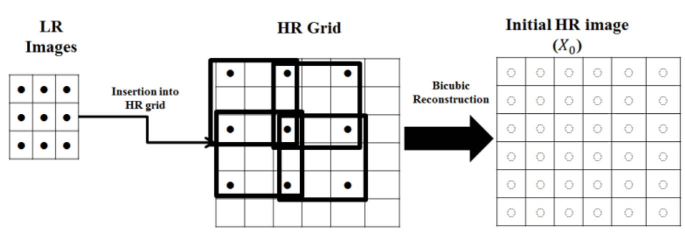

Fig. 2 Initial Imgae (X_0) reconstruction (Bicubic Interpolation)

Once an HR image is obtained, a restoration procedure is applied to reduce the blur and noise. Restoration can be performed by applying any deconvolution methods that considers the presence of the noise [1]. To preserve both edge information and smoothness of the image, we use an HF regularization term to reconstruct the final image as mentioned earlier.

B. Construction HF layer of X_0

The HF layer used in the reconstruction of the HR image is explained in this step. The proposed method provides a more accurate HF layer which can be added to the regularization term in order to preserve the edges of the MRI image in an iterative back projection scheme while the smoothness is maintained with the application of the Bicubic interpolation. In this step, X_0 the initial HR image is down-sampled to be the same size as Y which is the input MRI image. Note that the edges of X_0 are smoothed by interpolation process, therefore, subtraction of down-sampled X_0 from Y forms the edge information of the input MRI image ($E_{LR} = Y - X_0 \downarrow$). This self-example generation can easily reconstitute the edges of LR image (E_{LR}). Then, the Bicubic interpolation can be used to expand E_{LR} to HF layer of initial HR image (E_{HR}).

C. Iterative Back Projection Using HF Layer

As mentioned earlier, SR is an ill-posed inverse problem in the sense that the information contained in the observed LR images is not sufficient to reconstruct the HR image. Referring to Eq. (2), the ill-posed SR problem can be reformulated by minimizing the distance function δ between the observed and the estimated images [11]:

$$\hat{X} = \min_{X} \{\delta(Y, SHMX)\} \tag{3}$$

This can be rewritten as:

$$\hat{X} = \min_{X} \{\|Y - AX\|_2^2\} \tag{4}$$

where matrix $A = S \times H \times M$ is the degrading matrix that converts HR image to LR observation.

Eq. (4) is an ill-posed problem, therefore, there exist an infinite number of solutions for $\hat{X}$. In order to obtain a stable and a unique solution, a regularization term is usually introduced to compensate for the missing information with some general prior knowledge of the desired HR solution, e.g.,

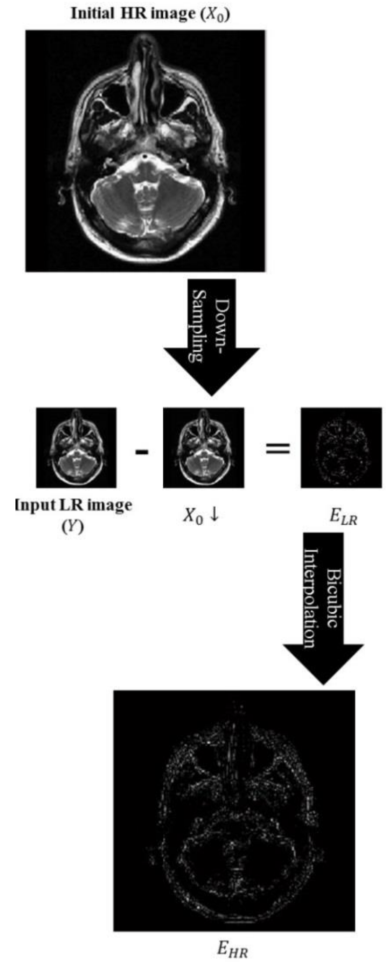

Fig. 3 Process of HF Layer construction

degree of smoothness. Specific regularization enforces additional constraints to remove artifacts from the final results. Therefore, Eq. (4) can be updated to the following form:

$$\hat{X} = \min_X \{\|Y - AX\|_2^2 + \lambda\psi(X)\} \tag{5}$$

where $\psi(X)$ is the regularization term and $\lambda \in [0,1]$ is a regularization parameter. The regularization term controls the balance between the distance function and the regularization term which is generally the smoothness of the solution. This paper presents a HF layer regularization in order to both preserve the edges while maintaining a smooth solution. The proposed method can improve the visual quality of the MRI image while being fast and appropriate for real time medical applications. The regularization term used in our method is enhanced by adding the E_{HR} term as following:

$$\hat{X} = \min_X \{\|Y - AX\|_2^2 + \lambda(\|\nabla X\|_2^2 + E_{HR})\} \tag{6}$$

In this way, the TV model using the L_2 norm can preserve the smooth areas by suppressing the noise, and E_{HR} is used to enhance the HF edge areas, i.e., Eq. (6) can preserve both smooth areas and edges at the same time.

The steepest descent optimization has been applied to find the solution to this minimization problem as follows.

$$X_n = X_{n-1} + \beta\left\{A^T(Y - AX) + \lambda \sum_{all\,x} \sum_{all\,y} \sqrt{\nabla x^2 + \nabla y^2} + \lambda E_{HR}\right\} \quad (7)$$

where $A = S \times H \times M$ is the degrading matrix, and β is a scalar defining the step size in the direction of the gradient.

IV. EXPERIMENTAL RESULTS

The proposed method has been implemented in MATLAB and its performance and simulation results are presented in this section. To evaluate the performance of the proposed method relative to others, we perform super-resolution reconstruction on well-known BrainWeb 3D MRI phantoms [12-13]. Our experiment consists of reconstructing down-sampled versions of HR T 1-weighted (T 1w) volume of voxels (voxel resolution 1 mm^3) that corresponds to the HR T 1w BrainWeb phantom. Down-sampled of the HR volume are available in the x, y, and z direction at different slice thickness (2, 3, 5, 7 and 9 mm). The resolution of all LR MRI images is extended in z direction to obtain HR 1 mm^3. The proposed method is also compared to the bicubic, nearest neighbor (NN) and B-spline (3rd order) interpolation methods. Fig. 4 shows the results of various methods for three different MRI images. The peak signal to noise ratio (PSNR) values for different techniques are obtained by comparing the reconstructed HR volume images relative to the original 1 mm^3 HR T 1w images.

Table 1 represents the average PSNR values of images with different slice thickness values for various methods. It is evident that the proposed method provides better visual quality in comparison with the others.

Fig. 5 shows that the average of PSNR values decrease when MRI image with lower resolution are converted to HR (voxel resolution 1 mm^3) images.

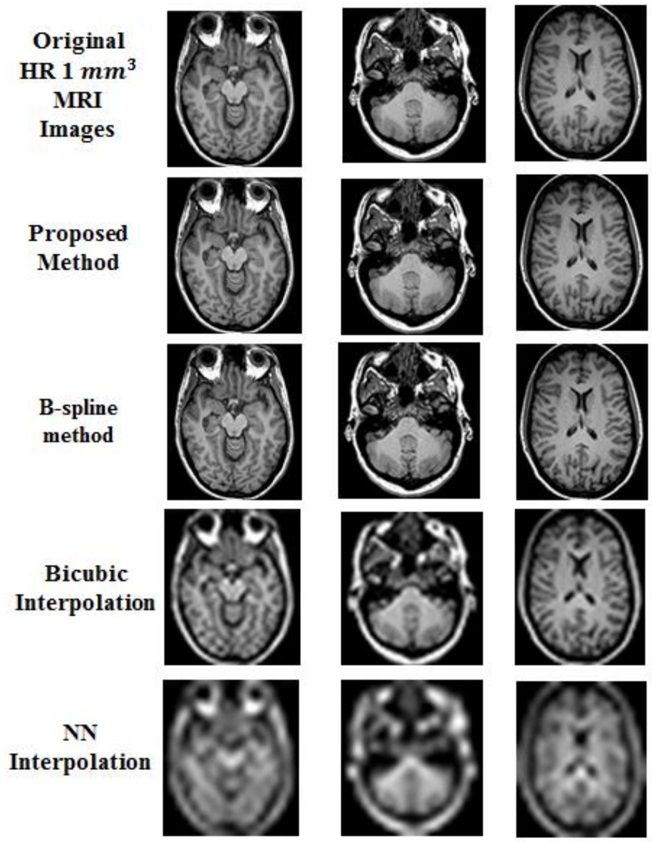

Fig 4. Results of SR for differnt methods

Table 1 The average of PSNR values for different slice tickness (LR images)

Slice Thickness	2 (mm)	3 (mm)	5 (mm)	7 (mm)	9 (mm)
Proposed Method	35.63	32.45	30.34	25.54	23.21
B-spline Method	34.98	31.85	30.12	25.01	22.89
Bicubic Interpolation	31.64	28.52	25.5	23.87	20.45
NN Interpolation	28.12	26.32	22.64	20.13	18.24

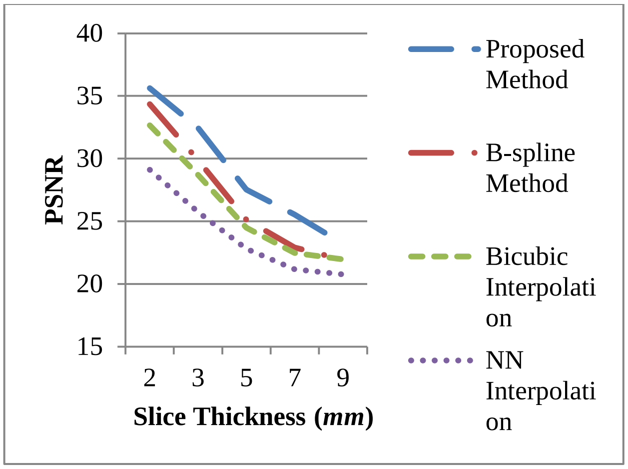

Fig 5. The average PSNR values for different methods decrease for lower resolution

V. CONCLUSION

In many medical applications, the acquired MRI images need to be up-sampled to match a specific resolution or providing more information. This paper presents a novel technique for resolution enhancement of MRI images which enables the recovery of the HR information from LR data. Traditionally, image interpolation techniques have been applied in these cases to improve the resolution. However, interpolation techniques tend to smooth images, therefore, they are not able to recover HF information. The proposed method using HF regularization has been shown to outperform classical interpolation schemes. The improved performance of the proposed method can be of value considering the limitations of the MRI images. Namely, acquiring multiple MRI images with small shifts is very time-consuming and not convenient for the patients. Also, following the generalized sampling theorem, sub-pixel oscillator frequency shifts do not add new information needed for SR reconstruction. For these reasons, the focus of the proposed technique is on single image enhancement.

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