

# Inter-slice Reconstruction of MRI Image Using One Dimensional Signal Interpolation

C.G.Ravichandran<sup>1</sup>, Dr.G.Ravindran<sup>2</sup>

<sup>1</sup> Research Scholar, Centre for Medical Electronics, Anna University, Chennai  
<sup>2</sup>Chariman Information and Communication Engineering & Director,  
Center for Medical Electronics, College of Engineering, Anna University, Chennai.

## Abstract

There are number of methods for creating high-quality till images from a low quality image sequences. These methods are formulated in the space domain and they require that the input be expressed in that format. Super-resolution, an open-ended research problem still hasn't made its place in Video Processing. It is still in its initial stage of research. In MRI reconstruction, based on super-resolution back-projection algorithm, the images obtained from sets of irregularly located frequency domain samples are combined into high resolution image. The super-resolution replaces usually applied direct averaging of low-resolution images. Even though the super-resolution based reconstruction produces very good results in terms of quality, the cost of such reconstruction process in terms of CPU time is very high. In this paper, one dimensional signal interpolation method has been implemented for inter-slice reconstruction of 2D MRI image. The result of the one dimensional signal interpolation method for inter-slice reconstruction of MRI image is highly comparable with the existing super resolution methods in terms of speed and quality.

## Key words:

*MRI, CPU, reconstruction, super-resolution, back-projection, signal interpolation*

## Introduction

### Magnetic Resonance Imaging

Magnetic resonance imaging (MRI) is a noninvasive, usually painless medical test that helps physicians diagnose and treat medical conditions. MR imaging uses a powerful magnetic field, radio waves and a computer to produce detailed pictures of organs, soft tissues, bone and virtually all other internal body structures. MRI does not use ionizing radiation like x-rays. Detailed MR images allow physicians to better evaluate parts of the body and certain diseases that may not be assessed adequately with other imaging methods such as x-ray, ultrasound or computer tomography. Currently, MRI is the most sensitive imaging test of the head, particularly in the brain in routine clinical practice.

MRI slices are usually thick due to hardware limitations. So a small set of 2D slices does not give a good isotropic

3D image. This results in resolution that is high in-plane and is low in the other direction. So it is necessary to reconstruct intermediate planes/slices for better 3D reconstruction.

High-quality images are assured only when the patient remains perfectly stand still while the images are being recorded. A person who is very obese may not fit into the opening of a conventional MRI machine. The presence of an implant or other metallic object often makes it difficult to obtain clear images and patient movement can have the same effect.

MRI generally is not recommended for patients who have been acutely injured. This is because traction devices and life support equipment must be kept away from the area to be imaged. Furthermore, the examination takes longer than other imaging modalities and the results may not be immediately available as is often necessary in trauma situations.

Also, MRI may not be as sensitive as CT in the detection of intracranial bleeding. Although there is no reason to believe that magnetic resonance imaging harms the fetus, the effects of a strong magnetic field are not well understood. For this reason pregnant women usually are advised not to have an MRI exam unless medically necessary.

MRI may not always distinguish between tumor tissue and edema fluid. It cannot detect calcium present in a tumor. Detection of calcium (in tumors or other issues) is limited with MRI. MRI typically costs more and may take more time to perform than other imaging modalities.

### Super Resolution

Super Resolution aims at reconstructing an image at a higher resolution than the set of original images from which it was derived. The core idea behind Super Resolution is to combine information contained in different images of the same scene. However, when taking images of a scene, the acquisition device often moves

which leads to a non-alignment of the different images. Therefore, it is necessary to align them perfectly to be able to combine the information. This is called as the registration process. Usually this process involves geometric component, photometric component, illumination or color balance.

Once the images are registered, the Super Resolution process, estimate the high resolution image from a low resolution. This implies the construction of a forward model which describes the measured data depending on the unknown high resolution image. Once this model is defined, the next step is to construct a cost function which will measure the closeness between the measured data and the desired solution. The high resolution is then estimated minimizing the cost function.

Generally, the rectifying the distortion of Image sequence using super resolution technique consists of two major steps.

- (1) Registration of a set of input MRI images and
- (2) Reconstruction of a high resolution image from them.

Patrick Vandewalle et al, 2004 proposed a frequency domain technique to precisely register a set of aliased images; a high resolution image is then reconstructed using cubic interpolation. B. Marcel et al, proposed a motion estimation techniques in the frequency domain of the Fourier transform has been used for rigid-body transformation. L. Lucchese et al, 2000 defined a new method for estimating planar roto-translations that operates in the frequency domain for all the image information. Patrick Vandewalle et al, 2003 presented a simple method to generate a new high resolution image with almost twice the resolution in each dimension from a set of low resolution under sampled and shifted images. Raymond S. Wagner et al, 2005 discussed super-resolution techniques in general and review the details of one such algorithm from the literature suited to real-time application on forward-looking infrared (FLIR) images. Hayit Greenspan et al, 2002, presented a method for MRI reconstruction using super-resolution and shown improvement of spatial resolution, when spatially-selective RF pulses are used for localization. In 2D multi-slice MRI, the resolution in the slice direction is often worse than the in-plane resolution. This method improved the signal-to-noise efficiency of the data acquisition and effectively breaks the limits on slice thickness posed by the physical properties of existing MR imaging hardware. Multiple image registration and reconstruction methods have been proposed in several works. Image sequence enhancement using sub-pixel displacement was proposed by D. Keren et al, 1988. A Frequency Domain Approach to Registration of Aliased Images with Application to Super-Resolution was developed by P. Vandewalle, et al, 2006. To evaluate the

algorithms, few MRI image sets which were obtained from Medical research institutes are used. The performance of the algorithm in terms of time and accuracy has been measured and analyzed.

In Super-resolution, motion estimation is used to estimate the pixel positions of the three images with respect to the 1st image. Note that these pixel positions would not be at integer values, but can take any real value. Once this information is calculated accurately, it is possible to project this information on a desired high-resolution grid. The rotation calculation and shift calculation for the above algorithms has been implemented as follows:

#### Rotation Calculation

There are two ways that can be used to carry out rotation estimation between low resolution images.

- Rotate individual images at all the angles and correlate them with the first image. The angle that gives the maximum correlation is the angle of rotation between them.

The method described above is computationally expensive, so a faster method is to calculate the image energy at each angle. This will give a vector containing average energy at each angle. The correlation of these energy vectors of different images will give the angle of rotation. The energy calculation could also be carried in frequency domain. A graphical representation shown below in figure 1 helps to illustrate the method clearly.

$$\text{Angle}_i = \max \text{index} (\text{correlation} (I_1(\theta), I_i(\theta)))$$

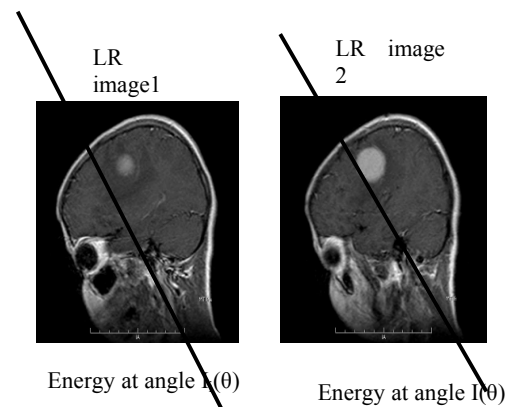


Figure 1 : Rotation Calculation

#### Shift Calculation

Once rotation angle is known between different images, shift calculation can be performed. Before calculating the shift, all the images are rotated with respect to the first image. Block matching was not used here because it is computationally expensive and need sub-pixel accuracy that is very hard to get with block matching. A much faster and reliable way to achieve this is using frequency domain method.

Technically, each frequency bin should give the same shift, but that does not happen. So, a least square method is used to estimate the shift  $\Delta s$ . As the LR images could be aliased, only 6% of the lower frequencies were used to calculate  $\Delta s$ .

Once we have a good estimate of shift and rotation between all the images and the reference image, we can find the pixel positions of all the Low Resolution images in the reference frame of the first image.

### Inter-slice Reconstruction of MRI Image Using One Dimensional Signal Interpolation

The following algorithm explains the Inter Slice Reconstruction using One Dimensional Signal Interpolation.

Convert the two dimensional image slices  $s_1$  and  $s_3$  into one dimensional image signal.

The following equation represents the signal corresponding to the input slice  $s_1$  as  $y_1=f(x_1)$

The intensity values of slice  $s_1$  are mapped to some pseudo index values.

The pseudo index values of  $x_1$  will be  $1, 3, 5, \dots, n$

The following equation represents the signal corresponding to the input slice  $s_3$  as  $y_3=f(x_3)$

The intensity values of slice  $s_3$  are mapped to some pseudo index values.

The pseudo index values of  $x_3$  will be  $2, 4, 6, \dots, n-1$ ,

The intermediate slice  $s_2$  can be represented by the equation as  $y_2$  for known  $x_2$ . Where the intensity values of the slice  $s_2$  which is proposed to be reconstructed are mapped to some pseudo index values. The pseudo index values of  $x_2$  will be  $1.5, 3.5, 5.5, \dots, n$

The interpolation using  $(x_1, y_1), (x_3, y_3)$  and  $x_2$  will yield a new  $y_2$ . Any non linear interpolation may be used by combining the two known  $x$  and  $y$  values  $(x_1, x_3)$  and  $(y_1, y_3)$  and use the known (assumed)  $x_2$ . we interpolate the middle layer values.

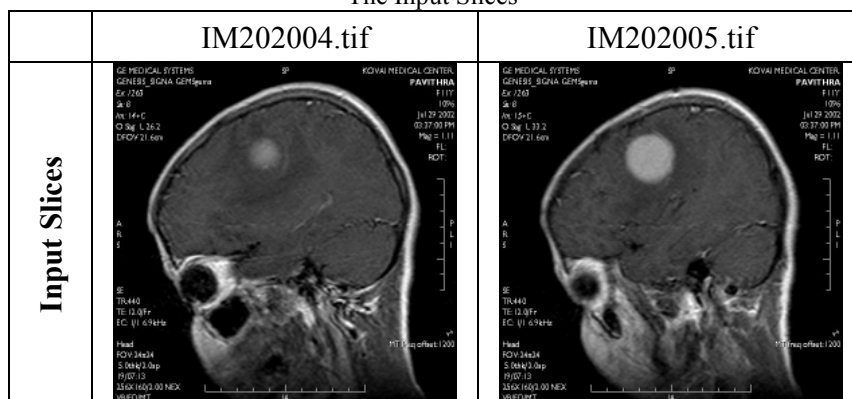
Let  $X_k = \{x_1, x_3\}$ , and  $Y_k = \{y_1, y_3\}$ ,  $y_2$  can be calculated as  $y_2 = I(X_k, Y_k, x_2)$ ;

Where  $I$  is the interpolation function.

### Implementation And Results

The super resolution based image distortion removal and inter-slice reconstruction system has been implemented using Matlab7 on a Pentium IV, 2 GH computer. The comparative results were presented below. MRI slices available with Matlab has been used as samples. The input slices and its inter-slice output using super-resolution methods and the one dimensional signal interpolation method are shown below in the figure 2

The Input Slices



The Reconstructed Slices

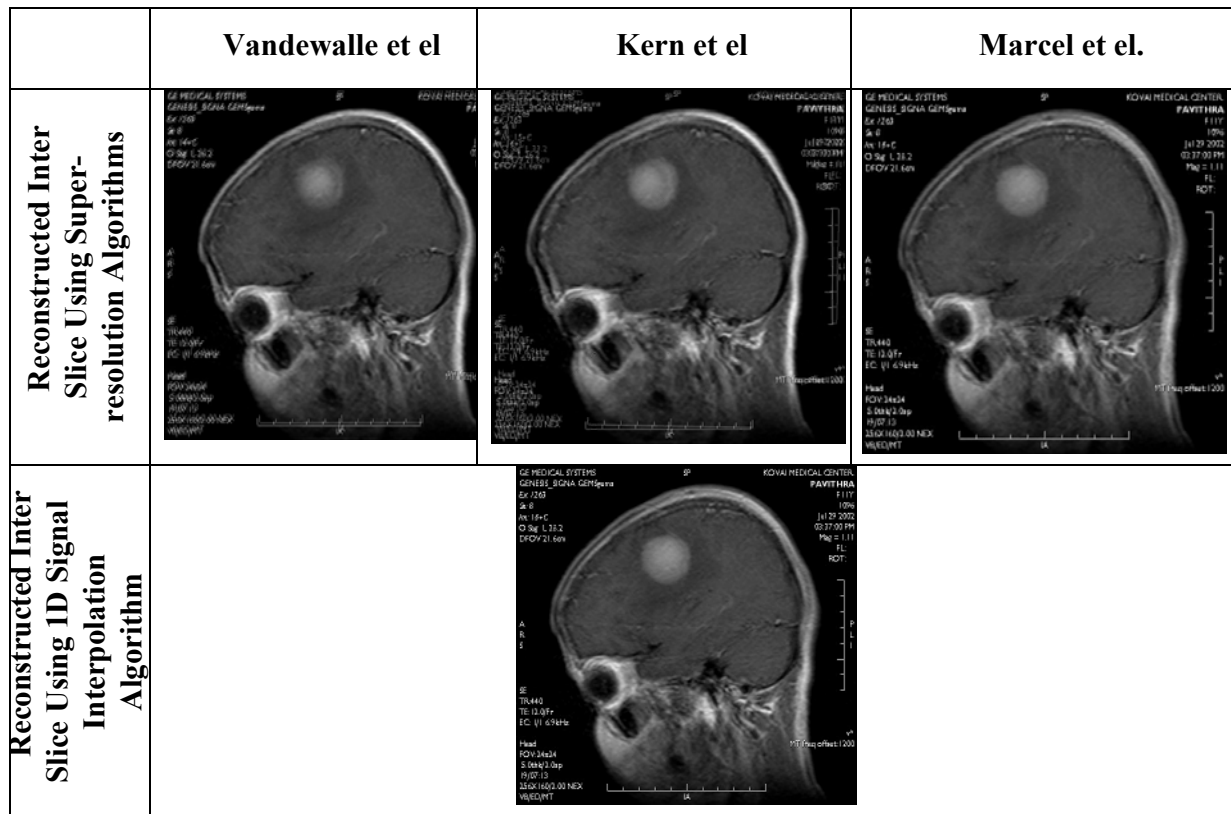


Figure 2. Inter-slice reconstructed Outputs

The following table 1 shows the performance of the three super resolution algorithms and one dimensional signal interpolation method.

Sl. No	Input slices	I. Time Taken For Inter Slice Reconstruction (sec)			
		Marcel et el.	Kern et el	Vandewalle et el	1D Signal Interpolation Method
1	MRISlice1.TIF MRISlice3.TIF	90.44	96.77	149.38	1.52
2	MRISlice2.TIF MRISlice4.TIF	91.34	97.04	150.23	1.46
3	MRISlice3.TIF MRISlice5.TIF	92.54	98.35	148.99	1.49
II.	<b>Average Time</b>	<b>91.44</b>	<b>97.39</b>	<b>149.53</b>	<b>1.49</b>

Table 1 : Performance in terms of Speed Size of the Slice 256x256

The following graph also shows the performance of the three implemented algorithms with input hand image of 256x256.

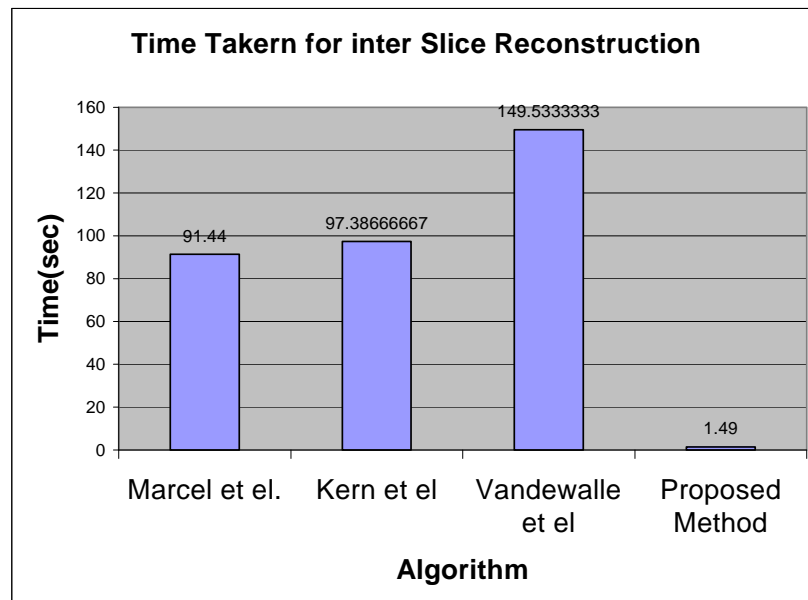
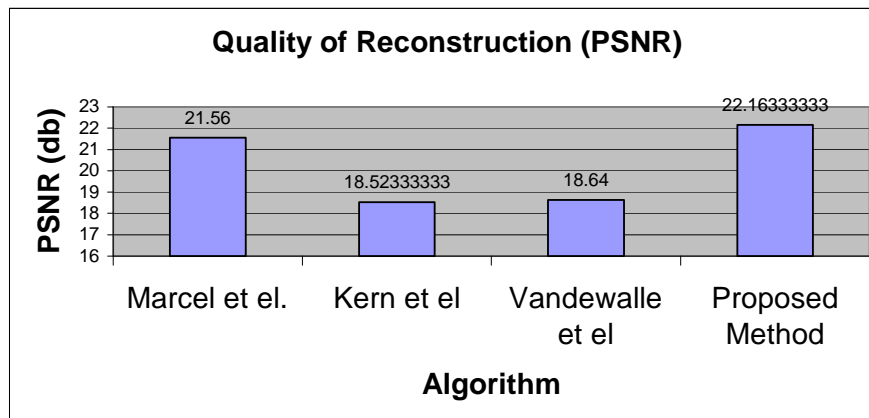


Figure 4. The Performance Graph

In the above graph, the x-axis shows the algorithms and in the y-axis, the time taken for Inter Slice Reconstruction is shown in seconds.

Sl. No	Input slices	III. PSNR (db)			
		Marcel et al.	Kern et al.	Vandewalle et al.	1D Signal Interpolation Method
1	MRISlice1.TIF MRISlice3.TIF	23.85	20.15	19.98	22.95
2	MRISlice2.TIF MRISlice4.TIF	19.49	15.97	16.93	21.63
3	MRISlice3.TIF MRISlice5.TIF	21.34	19.45	19.01	21.91
IV.	<b>Average PSNR</b>	<b>21.56</b>	<b>18.52</b>	<b>18.64</b>	<b>22.16</b>

The quality of reconstruction measured in terms of PSNR is shown below.



### Conclusion & Scope for Further Enhancements

The arrived results were more significant and comparable. The implementations were made successfully on Matlab and the performances of the algorithms were analyzed with suitable metrics. Some of the important observations are: 1. Image Registration is extremely essential for successful Super-resolution. 2. If the low-resolution images have redundant data, then Super-resolution does not work very well. 3. If the low-resolution images have all the information about the high-resolution, i.e. they have zero redundant data among them, and then Super-resolution works perfectly. One important fact about the algorithms doesn't require tweaking of many parameters, so same code works well for a wide range of images.

As far as the tests made with different images, the one dimensional signal interpolation based image reconstruction for shift and rotation estimation, performed very well in terms of speed and quality. The arrived results were significant and most promising. The performance of the algorithm makes it a real candidate for future research towards real-life implementations of the concept.

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