A Novel Approach for Super Resolution in Medical Imaging

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Abstract- The recent increase in the wide use of digital imaging technologies in consumer (e.g., digital video) and other areas (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 intended 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. 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. These High resolution images are frequently required in biomedical applications, because the HR images provide the accurate spatial and intensity information for correct diagnosis. In various MR imaging techniques, which are important for early medical diagnosis purposes.

Keywords- Algorithm, Biomedical, High Resolution, Low Resolution, MR imaging, Super-Resolution.

I. 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. Hence image enhancement is the key area for the researchers, especially to improve the resolution. Image resolution is defined as the smallest discernible or measurable detail in a visual presentation and the process of obtaining a high resolution image from a set of low resolution observations is called super-resolution imaging. It 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 [1]. In almost every application, it is desirable to generate an image that has a very high resolution. Thus, a high resolution image could contribute to a better classification of regions in a multi-spectral image or to a more accurate localization of a tumour in a medical image or could facilitate a more pleasing view in high definition televisions (HDTV) or web-based images. The resolution of an image is dependent on the resolution of the image acquisition devices. However, as the resolution of the image generated by a device increases, so does the cost of the device and hence it may not be an affordable solution. Therefore we are emphasizing our work to avoid hardware updating solution which is more costly and complex.

A. Imaging Problems

Medical images typically suffer from one or more of the following imperfections:

- Low resolution (in the spatial and spectral domains)
- High level of noise
- Low contrast
- Geometric deformations
- Presence of imaging artefacts

These imperfections can be inherent to the imaging modality (e.g. X-rays offer low contrast for soft tissues, ultrasound produces very noisy images, and metallic implants will cause imaging artefacts in MRI) or the result of a deliberate trade-off during acquisition. For example, finer spatial sampling may be obtained through a longer acquisition time. However, that would also increase the probability of patient movement and thus blurring.

B. Challenges in Super Resolution

Super resolution imaging is the process of obtaining HR image from the set of LR observations. The imaging system presents number of peculiar and challenging situations some of which are unique to brain MR image acquisition scenario.

i) Image registration: small image displacements are crucial for beating the sampling limit of the original camera or machine, but the exact mappings between these images are unknown. To achieve an accurate super-resolution result, they need to be found as accurately as possible.

ii) Magnetic field variation: when the images are aligned geometrically, there may still be significant magnetic field variation, because of different voltage levels or
machine exposure settings when the images were captured.

iii) Blur identification: due to patient movement blurs introduced in the image, these stages are modelled by a point-spread function (PSF) [2].

II. BRIEF LITERATURE SURVEY

A. Super Resolution

The central aim of Super-Resolution (SR) is to generate a higher resolution image from lower resolution images. High resolution image offers a high pixel density and thereby more details about the original scene. The need for high resolution is common in computer vision applications for better performance in pattern recognition and analysis of images. High resolution is of importance in medical imaging for diagnosis. Many applications require zooming of a specific area of interest in the image wherein high resolution becomes essential, e.g. surveillance, forensic and satellite imaging applications. However, high resolution images are not always available. This is since the setup for high resolution imaging proves expensive and also it may not always be feasible due to the inherent limitations of the sensor, optics manufacturing technology. These problems can be overcome through the use of image processing algorithms, which are relatively inexpensive, giving rise to concept of super-resolution. It provides an advantage as it may cost less and the existing low resolution imaging systems can still be utilized. Super-resolution is based on the idea that a combination of low resolution (noisy) sequence of images of a scene can be used to generate a high resolution image or image sequence. Thus it attempts to reconstruct the original scene image with high resolution given a set of observed images at lower resolution. The general approach considers the low resolution images as resulting from resampling of a high resolution image. The goal is then to recover the high resolution image which when resample based on the input images and the imaging model, will produce the low resolution observed images. Thus the accuracy of imaging model is vital for super-resolution and an incorrect modeling, say of motion, can actually degrade the image further. The observed images could be taken from one or multiple cameras or could be frames of a video sequence. These images need to be mapped to a common reference frame. This process is registration. The super-resolution procedure can then be applied to a region of interest in the aligned composite image. The key to successful super-resolution consists of accurate alignment i.e. registration and formulation of an appropriate forward image model. Most of the super-resolution image reconstruction methods consist of three basic components: (i) motion compensation (ii) interpolation and (iii) blur and noise removal. Motion compensation is used to map the motion from all available low resolution frames to a common reference frame. The motion field can be modeled in terms of motion vectors or as affine transformations. The second component refers to mapping the motion-compensated pixels onto a super-resolution grid. The third component is needed to remove the sensor and optical blurring.

B. MR Images

Magnetic resonance Imaging (MRI) is non ionizing technique that uses radio frequency (200 MHZ to 2GHZ) radiation and large magnetic field around 1-3 tesla. The large magnetic fields are produced by superconducting magnets in which current is passed through coils of superconducting wire whose electric resistance is virtually zero. MRI images provide anatomical & physiological detail, i.e. structure and function with full three dimensional capabilities excellent soft tissue visualization and high spatial resolution it is a topographic imaging modality. MRI scanners are several times as costly as a CT scanners because of the expensive superconducting magnet required. All such Medical imaging techniques produce very large amounts of data, especially from CT, MRI, and PET modalities. As a result for storage, communication and proper diagnoses of electronic images required super resolution of images. Magnetic resonance imaging, or MRI, is a way of obtaining very detailed images of organs and tissues throughout the body without the need for x-rays or "ionizing" radiation. Instead, MRI uses a powerful magnetic field, radio waves, rapidly changing magnetic fields, and a computer to create images that show whether or not there is an injury, disease process, or abnormal condition present. For this procedure, the patient is placed within the MR scanner typically a large, tunnel or doughnut-shaped device that is open at both ends. The powerful magnetic field aligns atomic particles called protons that are present in most of the body’s tissues. The applied radio waves then cause these particles to produce signals that are picked up by a receiver within the MR scanner. The signals are specially characterized using the rapidly changing magnetic field, and, with the help of computer processing, very sharp images of tissues are created as "slices" that can be viewed in any orientation. An MRI exam causes no pain, and the magnetic fields produce no known tissue damage of any kind. The MR scanner may make loud tapping or knocking noises at times during the procedure using earplugs prevents problems that may occur with this noise [3, 4].

C. History of the MRI

MRI is being most important system for correct diagnosis of disease. Now a days different configuration MRI machines are available in market. Though their cost is as higher but recently development and researches are going on to enhance the quality and reducing the MRI machine. The time line history and development of MRI system is given in brie as below.

- Felix Bloch and Edward Purcell (1946) - came up with the idea to use magnets to take pictures of a living being.
- Nuclear Magnetic Resonance (1950-1970) – during this period first analyzes molecules then taken
images of inside a body and the first brain MRI images took 72 hours to develop.

- Raymond Damadian (1971) - proved that magnetic resonance could be used to help detect diseases by the different nuclear magnetic relaxation times between tissues and tumors.
- The second MRI image was taken (1972). It was two dimensional which showed the length and width.
- Paul Lauterbur (1973) - demonstrated magnetic resonance imaging on test tubes.
- Dr. Raymond Damadian (1977) - completed the first whole body MRI scanner which he called "Indomitable", and performed the first whole body scan using Indomitable. It lasted four hours and 45 minutes to complete.
- In 1986 the time to receive an image decreased to five seconds.
- In 1993 the functional MRI was developed. The images showed the different regions of the brain.

D. Need of MRI

Magnetic resonance imaging (MRI) is done for many reasons. It is used to find problems such as tumors, bleeding, injury, blood vessel diseases, or infection. MRI also may be done to provide more information about a problem seen on an X-ray, ultrasound scan, or CT scan. Contrast material may be used during MRI to show abnormal tissue more clearly. An MRI scan can be done for the:

- **Head**: MRI can look at the brain for tumors, an aneurysm, bleeding in the brain, nerve injury, and other problems, such as damage caused by a stroke. MRI can also find problems of the eyes and optic nerves, and the ears and auditory nerves.
- **Chest**: MRI of the chest can look at the heart, the valves, and coronary blood vessels. It can show if the heart or lungs are damaged. MRI of the chest may also be used to look for breast or lungs cancer.
- **Blood vessels**: Using MRI to look at blood vessels and the flow of blood through them is called magnetic resonance angiography (MRA). It can find problems of the arteries and veins, such as an aneurysm, a blocked blood vessel, or the torn lining of a blood vessel (dissection). Sometimes contrast material is used to see the blood vessels more clearly.
- **Abdomen and pelvis**: MRI can find problems in the organs and structures in the belly, such as the liver, gallbladder, pancreas, kidneys, and bladder. It is used to find tumors, bleeding, infection, and blockage. In women, it can look at the uterus and ovaries. In men, it looks at the prostate.
- **Bones and joints**: MRI can check for problems of the bones and joints, such as arthritis, problems with the temporomandibular joint, bone marrow problems, bone tumors, cartilage problems, torn ligaments or tendons, or infection. MRI may also be used to tell if a bone is broken when X-ray results are not clear. MRI is done more commonly than other tests to check for some bone and joint problems.
- **Spine**: MRI can check the discs and nerves of the spine for conditions such as spinal stenosis, disc bulges, and spinal tumors [3, 4].

E. Advantages of MRI

1. MRI produces sectional images of equivalent resolution in any projection without moving the patient
2. MR image acquisition does not use ionizing radiation.
3. It requires little patient preparation and non-invasive, patient acceptability is high
4. MRI contrast agents are well tolerated and are much less likely than X-ray contrast agents to cause allergic reactions or alter kidney function
5. MRI provides information that differs from other imaging modalities. Its major technological advantage is that it can characterize and discriminate among tissues using physical and biochemical properties.

III. SUPER RESOLUTION RECONSTRUCTION MODEL

The above Figure 1 shows super resolution reconstruction model. Here Observed low resolution image sequence g(x, y), is reconstructed with the help of adaptive iterative transformation algorithm and compared the output images with other methods. An adaptive iterative transformation expression for obtaining \( f^* (x, y) \) as high resolution image is as follows

\[
\hat{f}^*(x, y) = g(x,y) - \left( \frac{2\eta}{\sigma^2} \right) \left[ g(x,y) - \text{ML} \right] \quad (1.1)
\]

Our proposed algorithm operates on a local region Sxy. Response of the algorithm is based on four quantities they are as follows

i. \( g(x,y) \) the value of noisy image at \((x,y)\)
ii. \( \sigma^2 \eta \) the variance of the noise corrupting \( f(x,y) \) to form \( g(x,y) \)
iii. \( \text{ML} \) the local mean of the pixels in \( \text{Sxy} \)
iv. \( \sigma^2 L \) the local variance of the pixels in \( \text{Sxy} \)

The detail steps of the super resolution reconstruction model are as follows:
i) Registration

In super resolution reconstruction the preprocessing task of utmost important is accurate registration of acquired images. It is process of overlaying two or more images of the same scenes taken at different time, different viewpoints and or different machines. Typically one image called the base image is considered as reference, to which the other images called input images are compared. The objective is to bring the input image in alignment with the base image by applying spatial transformation to the input images. Spatial transforms maps location in one image in to new location in another image. Image registration is an inverse problem as it tries to estimate from sampled images. It is also depend on properties of the machine used for image acquisition like sampling rate, imperfection of the lens that adds blur and the noise of the device. As the resolution decreases, local two dimensional structure of an image degrades and an exact registration of two low resolutions of images becomes difficult. Super resolution reconstruction required registration of high quality. The registration technique considered in our work is based on fast Fourier transform. For the registration of the images block techniques are used. The block matching techniques interpolate to given input image N times, compare image block of one MRI image to the other MRI image and then determine the displacement of 1/N pixels accuracy which gives the best similarity between the two blocks.

ii) Restoration

Image restoration is the process of the removal or reduction of the degradation which is occurred during the acquisition process. It may include noise, error in the pixel values or optical effect or machine effect such as out of focus or blurring or blurring due to patient movement or breathing. There are different methods here we have discuss for restoration using neighborhood operation wavelet etc but this techniques are complex and time consuming so here we have proposed the adaptive iterative transformation techniques for restoration. The detail mathematical steps of algorithm are explained below:

Step-1:- Low resolution blurred noisy under sampled images are considered as an input.

Step-2: The images are registered using FFT algorithm and calculate the FFT of image

1-D DFT of a signal x[n] over the interval [0: N-1]

\[ X(k) = X(2\pi \frac{k}{N}) = \sum_{n=0}^{N-1} x[n] e^{-j2\pi \frac{k}{N}} \]

Where k= 0, 1, 2… N-1

1-D IDFT of sequence x(k) gives a sequence x(n) on the interval [0:N-1]

\[ x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k] e^{j2\pi \frac{k}{N}} \]

Apply this to an image f(x, y) of size MxN

\[ S(k_x, k_y) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f[x, y] e^{-j2\pi \frac{k_x x + k_y y}{MN}} \]

The 2D DFT is

\[ f(x, y) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} S[k_x, k_y] e^{j2\pi \frac{k_x x + k_y y}{MN}} \]

Where Kx, Ky is frequency variables and x, y are spatial variables

Step 3:- Calculate frequency variables, phase angle, power spectrum of an image

1) Fourier spectrum

\[ |S(k_x, k_y)| = [R^2(k_x, k_y) + I^2(k_x, k_y)] \]

2) Phase angle

\[ \phi(k_x, k_y) = \tan^{-1}\left( \frac{I(k_x, k_y)}{R(k_x, k_y)} \right) \]

3) Power Spectrum

\[ P(k_x, k_y) = |S(k_x, k_y)|^2 \]

Step 4:- Calculate threshold value \( \alpha \)

\[ \alpha = K \frac{\mu}{\sigma} \]

Where, \( \mu \) = variance
\( \sigma \) = standard deviation
K = scaling factor

Step 5:- Construct new threshold (\( \alpha \)) value for next iteration

New \( \alpha = \alpha \times 1 - cc (i, j) / \text{Max}(cc) \)

Step 6:- Use property of separability for block by block process for image reconstruction

\[ S(k_x, k_y) = \sum_{x=0}^{M-1} e^{-j2\pi \frac{k_x x \text{ or } N}{MN}} \sum_{y=0}^{N-1} f[x, y] e^{-j2\pi \frac{k_y y \text{ or } M}{MN}} \]

\[ = \sum_{x=0}^{M-1} S[x, k_y] e^{-j2\pi \frac{k_x x \text{ or } N}{MN}} \]

\[ S(k_x, k_y) = \sum_{y=0}^{N-1} f[x, y] e^{-j2\pi \frac{k_y y \text{ or } M}{MN}} \]
Step 7: Apply inverse FFT to reconstruct image with New Alpha

Step 8: Rescale the image to Super Resolution level up to unit8

Step 9: Calculate the parameters of image PSNR, MSE, Time, etc.

\[
\text{PSNR} = 10 \log_{10} \left( \frac{P^2}{\text{MSE}} \right)
\]

\[
\text{MSE} = \frac{1}{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} [f(x,y) - g(x,y)]^2
\]

IV. EXPERIMENTATION

We have created two database namely (i) MRI_DB1 with 100 images, 10 each of same patient with different views (Top view, side view, back side view). Each image is JPEG, 8 bit gray scale, 512x512 with 96 dpi resolutions. (ii) MRI_DB2 of 50 images, 10 each of same patient with different views (Top view, side view, back side view). Each image is JPEG, 8 bit gray scale, 256x256 with 96 dpi resolutions. All these images are collected from Asian Heart Institute Mumbai, approximately 90% of the images are of good quality, while about 10% of the images are found of poor quality which are mainly due to limitation of MRI machine or cuffing and birthing problem of patient. Set of a few sample images acquired with 1.5T MRI machine from the databases MRI_DB1 and MRI_DB2 are explained in proposed result.

A. Results of Proposed Model

The Adaptive Iterative Transformation based Super Resolution Reconstruction Model used for restoration of low resolution images captured from 1.5T machines, gives the PSNR, SNR, MSE for super resolution of images as given in table 1 and 2 respectively for different threshold alpha values

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR</th>
<th>MSE</th>
<th>SNR</th>
<th>Time</th>
<th>Alpha</th>
<th>New alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>37.73</td>
<td>0.0427</td>
<td>13.7</td>
<td>6.97</td>
<td>0.0923</td>
<td>0.0904</td>
</tr>
<tr>
<td>2</td>
<td>35.9</td>
<td>0.0395</td>
<td>14.03</td>
<td>6.84</td>
<td>0.143</td>
<td>0.141</td>
</tr>
<tr>
<td>3</td>
<td>36.88</td>
<td>0.038</td>
<td>14.19</td>
<td>6.85</td>
<td>0.098</td>
<td>0.0962</td>
</tr>
<tr>
<td>4</td>
<td>36.40</td>
<td>0.035</td>
<td>14.12</td>
<td>6.25</td>
<td>0.093</td>
<td>0.091</td>
</tr>
<tr>
<td>5</td>
<td>37.07</td>
<td>0.044</td>
<td>13.53</td>
<td>8.28</td>
<td>0.116</td>
<td>0.115</td>
</tr>
<tr>
<td>6</td>
<td>37.71</td>
<td>0.038</td>
<td>14.18</td>
<td>6.75</td>
<td>0.062</td>
<td>0.061</td>
</tr>
</tbody>
</table>

Table 1: PSNR, Time and Alpha Values for MRI_DB1
i) Input image of 256x256 & Reconstructed Image of 512x512, by taking experimentation for Mean=0, Variance = 0.02 & σ=2

**Table 2:** PSNR, Time and Alpha values for MRI_DB2

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR</th>
<th>MSE</th>
<th>SNR</th>
<th>TIME</th>
<th>Alpha</th>
<th>New alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>35.73</td>
<td>0.07</td>
<td>10.93</td>
<td>6.69</td>
<td>0.076</td>
<td>0.078</td>
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<tr>
<td>2</td>
<td>35.83</td>
<td>0.018</td>
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<td>5.61</td>
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<tr>
<td>3</td>
<td>35.75</td>
<td>0.075</td>
<td>11.36</td>
<td>5.43</td>
<td>0.122</td>
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<tr>
<td>4</td>
<td>35.5</td>
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<td>12.1</td>
<td>5.25</td>
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<td>5</td>
<td>36.16</td>
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</tr>
<tr>
<td>7</td>
<td>36.22</td>
<td>0.066</td>
<td>13.01</td>
<td>5.16</td>
<td>0.133</td>
<td>0.125</td>
</tr>
<tr>
<td>8</td>
<td>35.92</td>
<td>0.078</td>
<td>11.15</td>
<td>5.94</td>
<td>0.14</td>
<td>0.13</td>
</tr>
<tr>
<td>9</td>
<td>36.7</td>
<td>0.08</td>
<td>11</td>
<td>5.36</td>
<td>0.141</td>
<td>0.125</td>
</tr>
<tr>
<td>10</td>
<td>36.71</td>
<td>0.085</td>
<td>10.92</td>
<td>5.44</td>
<td>0.145</td>
<td>0.12</td>
</tr>
</tbody>
</table>

The performance characteristic that is ROC curve for adaptive Iterative Transformation model for both database are shown in Figure .2(a, b, c, d, e) and Figure .3 (a, b, c, d, e) respectively As we have observed that for both database for low resolution images we can improve these image resolution by applying our proposed algorithm. The execution time for reconstruction is as shown in table .3 on P-IV processor.
With this, a high resolution image is reconstructed for both databases. The ROC characteristics curve shows that values of PSNR, MSE is acceptable.

V. CONCLUSION

The focus of the work in paper is on the resolution of images i.e. to improve the quality of degraded images, subsequent extraction of pixel splitting and smoothing of images. By taking a sample of low resolution image (blur, noisy, under sample) as input and reconstructed the super resolved image with the help of proposed Adaptive iterative transformed based method. We have design and implemented the super resolution reconstruction techniques which include pre-processing and post processing, which improve performance of Adaptive Iterative algorithm. Image post processing stage implemented to validate the resolution. The experimental results from the algorithm indicate that this adaptive iterative algorithm is effective for to improve quality of degraded images. Particularly with tikhnovo regularization methods the no of iteration required are very high for example an image of size 512x512, more iteration required it increases the computational time required for reconstruction of image. The proposed algorithm is based on Fourier transform which drastically reduces no of iterations. Less no of iterations effectively reduces the computational time required to reconstruct the super resolved image. Thus the algorithm proposed for processing on low resolution images. A novel Adaptive Iterative algorithm provide the adequate and acceptable accuracy even though the adaptive iterative algorithm is simple, efficient and satisfy the necessary requirement with less computational time for reconstruction of super resolved image. The proposed adaptive iterative transformed based algorithm is tested by adding blur 5dB to 30dB and noise with mean 0, variance 0.001to 0.05 respectively and rescaling it. Experimental results obtained shows that proposed method offers average PSNR of 38.76dB and computational time 5.46 second, which would be suitable for monitoring and diagnostic applications particularly for brain tumor. The ROC based performance analysis demonstrate that PSNR values increases and computational time decreases, hence clarity have been much improved by the proposed method. The result also shows that the proposed method performed well and clinically useful.

REFERENCES