A Novel Method for Brain MRI Super-resolution by Wavelet-based POCS and Adaptive Edge Zoom

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Abstract **– This paper aims to make the super-resolution of a high-resolution image from a sequence of low-resolution frames containing non-stationary objects. The challenges of making super-resolution image, like unavoidable smoothing effects, introduction of artifacts, computational efficiency in time and computational efficiency in memory requirements, are considered and a novel method is proposed to solve these problems. The proposed method handles the super-resolution process by using wavelet based projection-onto-convex-set with adaptive edge zoom algorithm. Adaptive edge zoom algorithm address the problem of producing enlarged picture from the given digital image. Wavelet based projection-onto-convex-set method is used to enhance spatial resolution of MRI brain images from a temporal sequence. This method produces more clarity with high peak signal-to-noise ratio.**

Keywords**-Super-resolution, Image, POCS, Wavelet, Adaptive Edge Zoom**

I. INTRODUCTION

In the medical field, digital image processing techniques are the most needed techniques for human organs separation, splitting the affected cancer tissues, finding disease captured area. More specifically super-resolution plays an important role for MRI Scan analysis. In medical images, doctors request to enlarge the human parts in images. So that they can view the bio-parts accurately and more close format.

Image super-resolution is to restore a high-resolution image from a sequence of low-resolution frames. It has also been used recently in improving MRI image quality by enhancing its spatial resolution. This paper concentrates on, How to get a super-resolution medical MRI image in the case of brain MRI [1]-[3]. For the same purpose it uses Haar wavelet based POCS (Projection-Onto-Convex-Set). For resolution increasing (Zooming) purpose it handles Adaptive edge zoom method.

The method developed by Youla [5], [6] introduces the Projection-onto-convex-set for image enhancement and restoration. This method is then practically followed by lot of researchers for the enhancement of super-resolution functionality [7]-[9], [16]. In the POCS process the targeted image is continuously updated (or enhanced) for super-resolution construction with a guaranteed convergence.

Producing an image into enhanced resolution from sequence of images at a lower resolution is commonly spelled as Multi-frame super-resolution. The spatial correlations among successive frames in a temporal sequence and combining the non-redundant information, achieves the reconstruction at a higher resolution (in a better level). Some recent developments are done in the concept of, combination of wavelet with POCS [10]-[13], [15]. In wavelet based POCS method the wavelet coefficients are continuously replaced with the neighbor image wavelet coefficient.

This paper proposed an enhanced method for medical image super-resolution in a better way. This method combines the wavelet based POCS with Adaptive edge zooming [14]. Here we aim the super-resolution of human brain MRI images.

The rest of the paper is organized as follows. Section 2 provides steps of the proposed method. Section 3 reports the results obtained together with a discussion. A conclusion section ends the paper.

II. PROPOSED METHOD

This method presents a study of applying an image super-resolution method to enhance spatial resolution of MRI Brain images from a temporal sequence. This method uses a wavelet-based projection-onto-convex-set super-resolution reconstruction.

The main steps of the proposed method are as follows and they are explained one by one.

- Adaptive edge zooming on temporal sequence of Brain images.
- Projections-onto-convex-sets for Brain_0, Brain_1 and Brain_2.
- Wavelet-Based POCS Super-resolution.
- Enhancement by sub-image.

A. *Adaptive edge zooming on temporal sequence of brain images*

Three images are taken as input named Brain_0, Brain_1 and Brain_2. The zeroth image is selected via browse dialog. The input image is in Jpeg format of size 256×256. That brain MRI image is read and the pixel values are stored in the array format. Then they are converted into gray scale format using the formula.

GrayImage(i,j) = 0.299*redChannel(i,j) + 0.587*Green Channel(i,j) + 0.114*blueChannel(i,j)

This method zooms the input image to the specified size. The algorithm is explained in step by step format as in the following lines.

Step 1: The first step is the simplest one and requires expanding the source n × n *pixels* image onto a regular grid of size (2n – 1) × (2n – 1). More precisely if S(i, j) denotes the pixel in the i-th row and j-th column of the source image, and Z(l, k) denotes the pixel in the l-th row and k-th column in the zoomed picture as a mapping E: S→Z according to the equation E(S(i,j))= Z(2i-1,2j-1) as shown in Fig. 1.

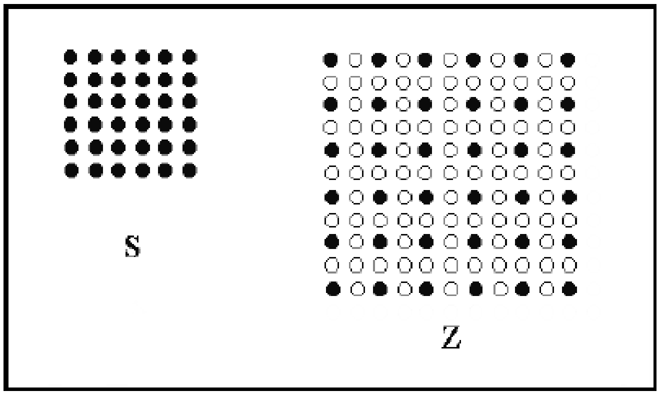
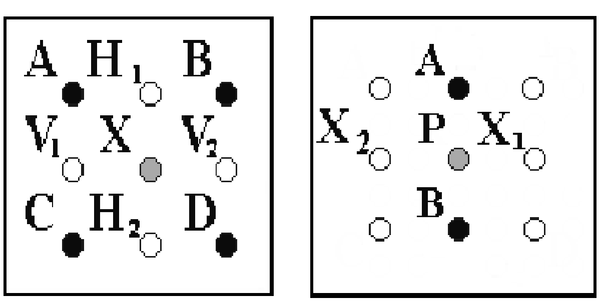


Fig. 1: First step of zooming (expansion)

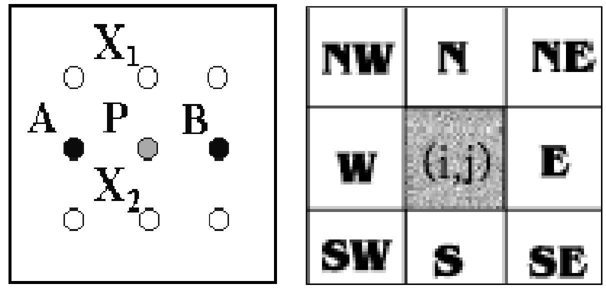
Step 2: The mapping E leaves undefined the value of all the pixels in Z with at least one even coordinates (white dots in Fig. 2). In the second step the algorithm scans line by line the pixels in Z whose coordinates are both even. These are the pixels denoted by a gray dot labeled with an X in Fig. 2a. For reference, in the following description we will use the capital letters A, B, C and D as in Fig. 2a, to denote the pixels surrounding the pixel X and that have already been assigned a value in the previous step (black dots). With letters a, b, c and d we denote the luminance value of pixels A, B, C, and D respectively. T1 = 150 and T2 = 70 are suitable thresholds. Direction mapping to reconstruct the pixel is given in Fig. 2d. For every X pixel one of the following mutual exclusive conditions is tested and a consequential action is taken:

- *(uniformity)*: range(a,b,c,d) < T1, then X= (a+b+c+d)/4.
- *(edge in SW-NE direction*): |a-d | > T2 and |a–d| >= | b – c | then X= (b + c)/2
- *(edge in the NW-SE direction*): |b-c| > T2 and |b–c| >= |a–d|,then X=(a + b)/2.
- *(edge in the NS direction)*: | a – d | > T1 and | b – c | > T1 and (a – d) * (b – c) > 0 then H1=(a + b)/2 ,H2=(c + d)/2 , and leave X undefined.
- *(edge in the EW direction)*: | a – d | > T1 and | b – c | > T1 and (a – d) * (b – c) < 0 then V1= (a + c)/2 V2 = (b + d)/2 to and leave X undefined.

Notice that at the end of this step there may be several X pixels, as well as several H1, H2, V1 and V2 pixels, left with an undefined value.



(a) (b)



(c) (d)

Fig. 2: (a) Layout of the pixel to reconstruct; (b) and (c) notation referred in the description of the algorithm. (d) Direction mapping

Step 3: In the third step the algorithm scans line by line image Z looking for pixels left undefined in the previous step and with at least one odd coordinate. These are the pixels denoted by the gray dot with label P in Fig. 2b and 2c.

- *(X1 or X2 have not been assigned a value) :I*f |a–b|<T1, then P = (a+ b) /2 , otherwise the value of pixel P is left undefined.
- *X1 and X2 have both been assigned a value): C*hecks for the presence of a vertical or an horizontal edge.
- *(presence of an edge in direction X1X2) | a –*b | > T2 and | a – b | >= | x1 – x2 | then P= (x1 + x2)/2 .
- *(presence of an edge in direction AB) :| x1 –* x2| > T2 and | x1 – x2 | >= | a – b | then P=(a + b)/2 .

Step 4: Using the information gathered in so far, in the next step the remaining "holes" is eventually filled. The fourth and final step of the algorithm scans once more picture Z looking for pixels with undefined value and fix the "hole" using a suitably median value. This "trick" guarantees a better detail preservation in the zoomed picture. Now the input gray image is enlarged.

The next image Brain_1 is selected via the browse dialog. This jpeg image is then converted into gray scale image. Then adaptive edge zoom method is adapted to the gray Brain_1 image. Similarly the above steps are repeated to image Brain_2.

The basic idea of this zoom is, to perform a gradient-controlled, weighted interpolation. However, it does not require a preliminary gradient computation because the relevant information is collected during the zooming process.

B. Projections-onto-convex-set on brain_0, brain_1 and brain_2

The POCS method giving a solution to the super resolution (SR) reconstruction problem [5, 6]. Consider that the motion information is provided, a data-consistency constraint set is defined based on the image formation model [5, 6]. The steps of POCS are listed below.

Step1: Let us assume Z_1 as Zoomed Brain_image_1 and Z_2 as Zoomed Brain_image_2. The low resolution image size is 256 x 256 (m, n). The high resolution image size, we assume is 512 x 512 (M, N). Then motion value calculation can be

$$M2 = \left(\sum_{\substack{i=0 \text{ to } M-1 \\ J=0 \text{ to } N-1}} Z_1(i,j) - Z_2(i,j) \right) / (M \times N)$$

Step 2: Then Gaussian kernel is applied on the Zoomed Brain_image_1 (Z1). For convolution the following 3x3 kernel is used:

$$\begin{matrix} 1 & 3 & 1 \\ 3 & 4 & 3 \\ 1 & 3 & 1 \end{matrix}$$

Step3: Residual_Image_for_1_and_2 (r2) can be calculated using the following equation:

$$r_2(i, j) = Z_1(i,j) - Z_2(i,j) \quad \text{where } i = 0 \text{ to } M,\ j = 0 \text{ to } N$$

Step4: The zoomed brain_1 image is updated (Blur removed) using the following rules:

$$Z_1(i, j) = Z_1(i, j) + \begin{cases} (r2-\Delta_0) \times (M_2/255), & r_2 > \Delta_0 \\ (r2+\Delta_0) \times (M_2/255), & r_2 < -\Delta_0 \\ 0, & \text{Other} \end{cases}$$

The bound Δ_0 is determined from the noise statistics [4, 5].

Step5: All the steps from 1 to 4 are repeated for the images Zoomed_Brain_1 (Z_1) and Zoomed_Brain_0 (Z_0). In this way we get the blur removed Brain_image_1 (Z_1).

C. *Wavelet-based POCS super-resolution*

This section combines the high frequency information hidden in a group of low resolution frames adjacent to the reference frame. The discrete wavelet method is adopted on the updated image Z_1. Haar family wavelet is adopted in this paper. Single level wavelet construction with haar is considered here. The process of haar wavelet is indicated in the following Fig. 3.

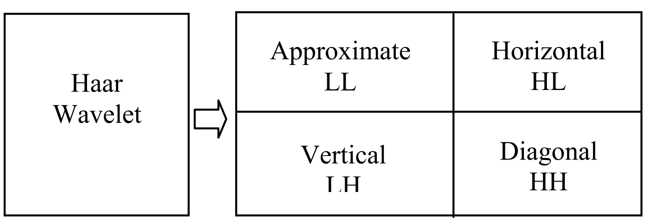


Fig. 3: Haar DWT Process

Here approximation is the coefficients in the LL band and detail means wavelet coefficients in the LH, HL and HH bands. So we define a wavelet projection as

(Approximation of $Z_1 \leftarrow$ low resolution image).

Here the measured low resolution image (the equivalent scaling coefficients), instead of the decomposition scaling coefficients, is used in the iterated reconstruction of Z_1.

Then the Inverse wavelet transform (Inverse Haar) is done on the approximation-replaced-construction-image.

D. *Enhancement by sub-image*

The horizontal sub-image of the wavelet construction is used to enhance the output of blur removed image. The algorithm steps are listed below:

Steps in Algorithm:

Step 1: Extraction of Horizontal sub-image of the wavelet construction.

Step 2: Gauss filter is implemented on that.

Step 3: Adaptive edge zoom is adopted on that.

Step 4: Quarter of that image data values are added with the updated SR image.

This MRI image is more informative model than the normal type zooming model.

III. EXPERIMENTAL RESULTS

In this paper we use the brain-image-sequences as input images. The image format we used in this paper is Jpeg format. The dimension of low resolution image is 256 x 256. The image sequence can be viewed in Fig. 4. Dimension of high resolution image is 512 x 512. The image sequence can be viewed in the Fig. 5.

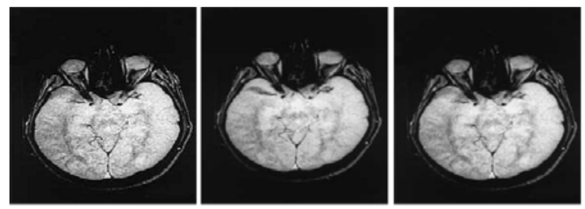


Fig. 4: Input Brain image sequence in the dimension 256 x 256

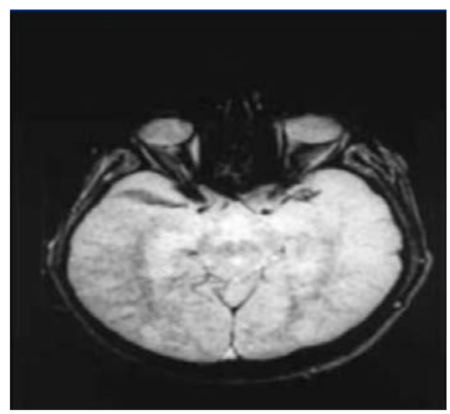


Fig. 5: Super-resolution image of brain MRI in the dimension 512 x 512 for the proposed method

For analysis purpose the 'Bilinear zooming process based high-resolution method' is also adopted (Fig. 6). The time taken for three different sets of brain-image-sequence is listed in table 1.

TABLE I

TIME TAKEN FOR 3 SET OF BRAIN SEQUENCES

Brain-Sequence	Bilinear method Time taken	Proposed-method Time taken
Set1	3.1739	5.733
Set2	3.054	5.527
Set3	2.825	5.738

TABLE III

PSNR FOR 3 SET OF BRAIN SEQUENCES

Brain-Sequence	Bilinear method PSNR	Proposed-method PSNR
Set1	9.147	29.347
Set2	11.052	28.776
Set3	9.130	26.021

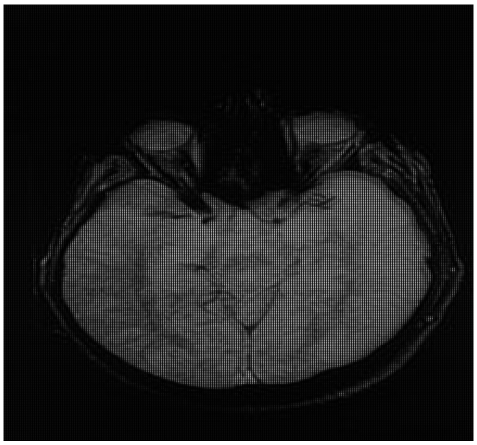


Fig. 6: High-resolution image of brain MRI in the dimension 512 x 512 for the Bilinear method

The MSE (Mean square error) value is calculated for three sets of brain sequences and tabulated in table 2. From the table 2 it can be proved that the proposed method yields low MSE values. So the image restoration in the proposed method is better than the existing method.

TABLE II
MSE FOR 3 SET OF BRAIN SEQUENCES

Brain-Sequence	Bilinear method MSE	Proposed-method MSE
Set1	7912.0977	75.567
Set2	5102.662	86.183
Set3	7944.596	162.5427

The PSNR is calculated for three sets of brain sequences and tabulated in table 3. From the table 3 it can be proved that the image restoration in the proposed method is efficient than the existing method, which has been compared in chart 1.

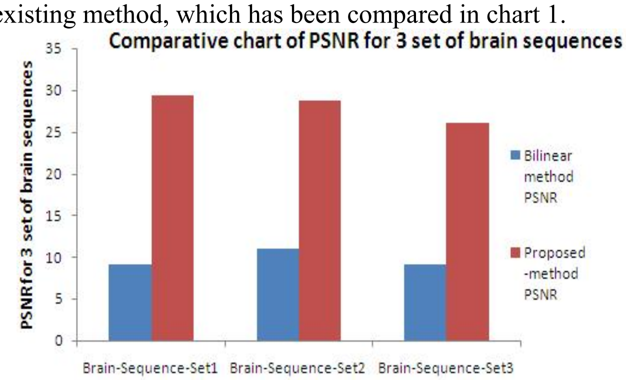


Chart 1: Comparative chart of PSNR for 3 set of brain sequences

IV. Conclusion

The proposed method makes the low resolution MRI brain image into a super-resolution one. Normally the MRI scanners are taking more time for additional resolution. This time taken problem can be solved using this robust method. Also the high resolution scanners in MRI field are much cost. This over-investment challenge can be solved greatly by this proposed super-resolution method.

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