3D Medical Image Enhancement based on Wavelet Transforms

Amir Yavariabdi
amir.yavariabdi@u-clermont1.fr

Chafik Samir
chafik.samir@u-clermont1.fr

Adrien Bartoli
adrien.bartoli@u-clermont1.fr

ALCoV-ISIT
Université d'Auvergne
Clermont-Ferrand, 63000
France

Abstract

This paper studies 2D and 3D wavelet domain medical image resolution enhancement method. The proposed approach is based on the interpolation of the low resolution input image and the derived high frequency sub-band images obtained using Discrete Wavelet Transform (DWT). Experimental results on both 2D and 3D images show how our method enhances the image's details and preserves edges.

1 Introduction

In recent years, the demand for resolution enhancement of pictorial data in medical images has been increased in order to assist clinicians to make accurate diagnosis. The tasks of resolution enhancement in medical images is generally to enlarge a region of interest. However, the main issue of concern is preserving more details in the enlarged image. In general, interpolated images have some problems such as losing the contrast and blurring the details. Thus, a robust medical image resolution enhancement technique must be able to cope with these two issues.

Nearest neighbor, bilinear and bicubic are the most well known interpolation techniques. However, the wavelet transform is playing a significant role in image resolution enhancement and many algorithms have been using it recently. Among other works, Chang *et al.* [2] and Carey *et al.* [1] have attempted to estimate the significant coefficients by examining the evolution of a wavelet transform's extrema among the same type of sub-band. The significant coefficients were used to improve the sharpness of the enhanced resolution image and edge detection algorithm were used to create a model for detecting edges in higher frequency sub-bands. Only coefficients with significant magnitudes were estimated as the evaluation of the wavelet coefficients. Temizel *et al.* [6] applied wavelet domain zero padding in order to generate an initial high resolution approximation. Such approximation usually involves smoothing and ringing that could be resolved by applying a cycle spinning methodology.

Our aim in this paper is to propose a method for 3D image resolution enhancement based on discrete stationary wavelet transforms to generate sharp high resolution images. More specifically, we first increase the quality of edges using a shape function [7] and then use both the discrete and the stationary wavelet transforms to decompose the resulting image into low and high frequency sub-bands. The proposed method shows that the results obtained in [3], in the 2D case, could be further improved by considering the mean of the high frequency sub-band coefficients. To assess the efficiency of our method, we have considered comparisons with some conventional and state-of-art image resolution techniques such as bi-linear, bicubic, Wavelet Zero Padding (WZP), Discrete Wavelet Transform-Based Image Resolution Enhancement [4], and Image Enhancement by using Discrete and Stationary Wavelet Decomposition [3]. Note that the 2D version of the proposed method outperforms

the state of the art and its extension to 3D enhancement based on wavelet transforms is completely new to the best of our knowledge.

The rest of the paper is organized as follows. Section 2 is a brief review of previous image enhancement work. Section 3 presents the proposed method to enhance image resolution. Results and discussions are provided in section 4 and the paper is concluded in section 5.

2   Image resolution enhancement

There are various wavelet based methods which have been used for medical image resolution enhancement. However, just two state-of-art techniques have been implemented for comparison purposes. The first technique is DWT-based resolution technique [4], and the second one is image resolution enhancement by using DWT and Stationary Wavelet Transform (SWT) [3].

DWT-based image resolution enhancement   The method consists of combining high frequency sub-bands using DWT and the input low resolution image to achieve a sharper result. The method can be summarized as follows:

- *use DWT to decompose the input image into sub-band images*

- *apply bicubic interpolation to sub-band images*

- *subtract the low frequency sub-band image from input low resolution image*

- *add the difference image to high frequency sub-bands*

- *apply bicubic interpolation to above estimated detail coefficients and low resolution input image to reach the required size for inverse DWT.*

Image resolution enhancement by using DWT and SWT   In this method one level DWT is employed to decompose the input image into four different sub-band images. The three high frequency sub-bands images which contain the high frequency components of the input image are interpolated by bicubic interpolation. Furthermore, SWT has been employed to minimize information loss due to the downsampling in DWT. This is followed by combining all the high frequency sub-band images to generate new corrected high frequency sub-band images. Note that, the input image and the new corrected high frequency sub-band images can be interpolated for higher enlargement. Finally, inverse DWT is applied to create the high resolution image.

3   Proposed algorithm for 3D images

As already stated, smoothing caused by interpolation techniques create a serious problem on edges. Hence, preserving edges must result in better output images. The complete block diagram of the 2D proposed algorithm is illustrated in Figure 1. In order to apply the proposed algorithm to 3D images, the 3D DWT has been chosen to preserve the edges. In the proposed algorithm, one level DWT is applied to decompose a 3D low resolution image into eight different sub-band images. The high frequency sub-bands such as HHH, HHL, HLH, LHH, LHL, LLH, and HLL (where H and L are High and Low coefficients) contain the edges of the low resolution image. Furthermore, the size of high frequency components of DWT is increased by 3D bicubic interpolation with factor 2. Note that downsampling of sub-band images in DWT cause the information loss in the sub-bands. Thus, 3D SWT is employed to reduce this information loss. While the high frequency sub-bands in both DWT and SWT have the same size their mean must be computed to correct all the high frequency sub-band coefficients. For higher enlargement, the bicubic interpolation technique can be applied to
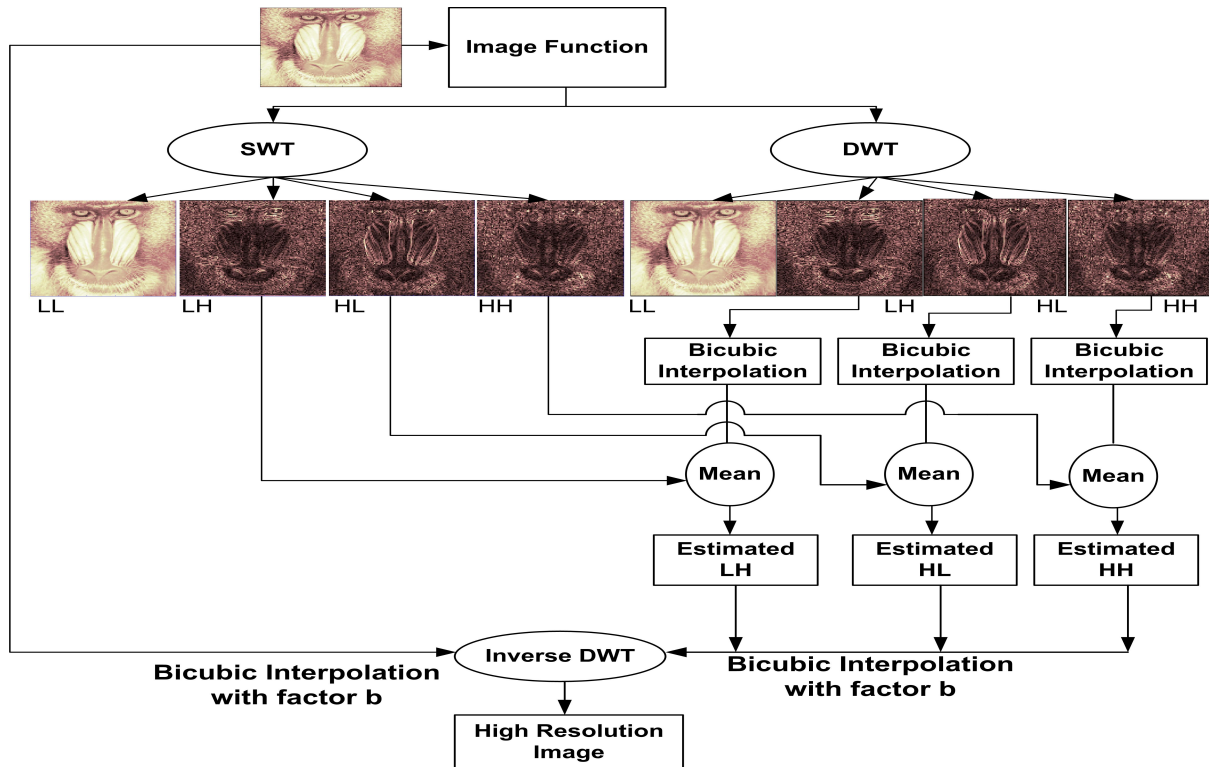
Figure 1: The Block Diagram of the 2D Proposed Algorithm.

the new corrected high frequency sub-bands. It is worth to note that the low resolution image is created by low-pass filtering of the high resolution image [5]. As mentioned before, the shape function which has been explained by Tai *et al*. [7] applied to the input low resolution image to enhance the edge intensities. Thus, it results in preserving more edge information while the proposed method estimates the coefficients. Accordingly, in order to increase the quality of the enhanced image, the improved input image is used instead of using the low frequency sub-band which contains less information than the original high resolution image. Also by interpolating the input image and the estimated high frequency components with factor ($\frac{b}{2}$), the 3D inverse DWT produces a sharper high resolution image than the interpolated image obtained by interpolation of the input image directly. This is due to the fact that the proposed method preserves more high frequency components after the corrections obtained by computing the mean of high frequency sub-bands than interpolating the input image directly.

4 Experimental result

In this section, the proposed method is discussed and compared with other resolution enhancement techniques. We will use 2D natural images, 2D slices of 3D volumetric MRI images, and 3D MRI images (S01, S02, S03), as shown in Table 2 and Figure 3. As a ground truth for accuracy evaluation purposes we consider a high resolution version of these gray level images with a size of 512×512 for 2D images and $512 \times 512 \times 24$ for 3D images. The high resolution images were downsampled by a factor of 4 to create low resolution images.

The error between ground truth and reconstructed images is expressed in terms of the peak signal-to-noise ratio (PSNR) values. PSNR, which has been generally applied for quality measurement in the field of image processing, can be defined by the following expression:

$$PSNR = 10\log_{10}\frac{255 \times 255}{\frac{1}{HW}\left(\sum_{i=1}^{H}\sum_{j=1}^{W}\left(I_1(i,j) - I_2(i,j)\right)^2\right)} \quad\quad (1)$$

where H and W are respectively the height and the width of the original high resolution image I_1 and enhanced image I_2.

The PSNR values for 2D images are given in Table 1 for four times enlargement. This table evaluates the accuracy of the proposed method with conventional and state-of-art resolution enhancement techniques. It is clear from Table 1 that the proposed method outperforms the other methods. Figures 2 confirms that the reconstructed images using the proposed technique in (d), comparing to the other methods in (b) and (c), improved the portrayal of salient image feature such as edges and contours.

Table 2 (Left) is a comparison between the 2D version of our method and the state of the art, both applied on a set of 2D MRI slices. The values in each row are obtained as a mean over the PSNR value on each slice. In order to have a comparison with the 3D version of our method, Table 2 (Right) shows the mean PSNR values computed over the 24 slices for each 3D image.

For display purposes, the proposed algorithm was applied to the full 3D MRI image volume (S01) shown in Figure 3 (a) to illustrate the original low resolution image with a size of $128 \times 128 \times 6$. Low resolution Slices are shown in Figure 3 (b). In Figure 3 (c) the proposed algorithm was applied to the 3D low resolution image in order to enhance the resolution to a full isotropic $512 \times 512 \times 24$ image; the resulting 2D slices are shown in Figure 3 (d). The PSNR results in Table 1 and 2 and the simulation results in Figures 2 and 3 show that the proposed method has sharper edge features, more details, and visually it is closer to the original image compared to the conventional and state-of-art image resolution enhancement results.

Method	Lena	Baboon	Head	Brain
Bi-linear	22.27	20.09	25.93	23.64
Bicubic	24.03	21.63	27.09	24.96
WZP (Db. 9/7)	25.76	21.99	29.81	26.07
discrete and stationary wavelet decomposition [3]	26.94	22.61	30.12	28.02
DWT based image resolution enhancement [4]	29.09	22.84	31.31	28.86
Proposed method	30.81	25.16	32.26	30.33

Table 1: PSNR (dB) Results for $4\times$ Resolution Enhancement (from 128×128 to 512×512).

Method	S01	S02	S03
Bi-linear	20.31	19.01	20.65
Bicubic	20.36	19.06	20.74
DSWD [3]	22.81	21.08	23.28
DWT [4]	26.83	25.25	27.23
Our method	27.46	26.51	28.60

Method	S01	S02	S03
Bi-linear	26.82	25.45	27.12
Bicubic	26.89	25.55	27.24
DSWD [3]	28.20	27.38	29.07
DWT [4]	33.49	32.13	34.72
Our method	34.57	33.40	35.71

Table 2: Average PSNR (dB) for Left: 2D Slices; Right: Overall Slices of 3D Images.

5   Conclusion

A new 3D wavelet domain image resolution enhancement technique has been presented. The proposed technique applies a shape function to the input low resolution image in order to enhance the discontinuities and then uses both DWT and SWT to estimate unknown detail coefficients. It has been tested on 2D images to show its performance against state-of-art methods and on 3D MRI images. Comparisons based on PSNR and visual results demonstrate that the proposed method provides the best result in terms of PSNR.
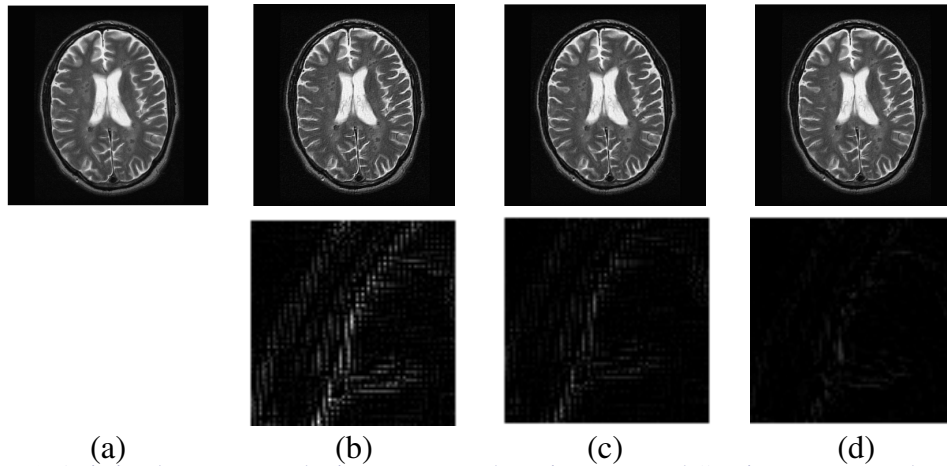
Figure 2: (a) Original Low Resolution Image, (b) Discrete and Stationary Wavelet Decomposition; (c) Discrete Wavelet Transform-Based Image Resolution Enhancement; (d) Proposed Technique and the Residual Images of the Close-up Scene for Specific Block Size in the Second Row.
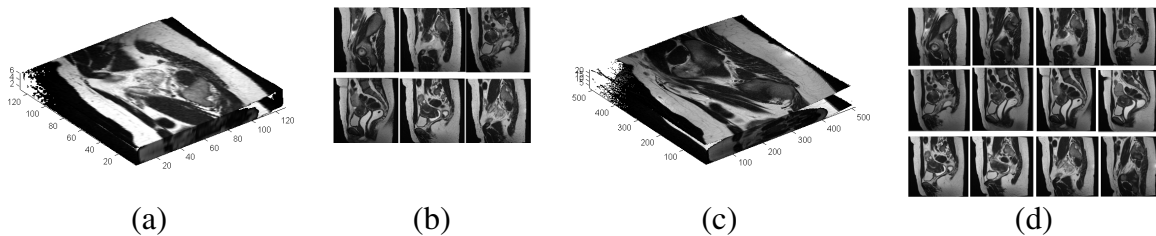

Figure 3: (a) 3D Original Low Resolution Image (S01), (b) 2D Slices of 3D Low Resolution Image, (c) 3D Enhanced Resolution Image, (d) Odd 2D Slices of 3D Enhanced Resolution Image.

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