Image Zooming using Wavlet Trnsfform haar & db4

Amol U Gawner
KSSED Polytechnic College Rakshi, Shevgaon

Samal Gadhe
KSSED Polytechnic College Rakshi, Shevgaon

ABSTRACT
Here we are implementing a method to zoom given image in wavelet domain.To zoom an image, concepts of multiresolution analysis along with zerotree philosophy is used. The wavelet transform has been identified as an effective tool for time-frequency representation of signals. It can decompose a digital image into some frequency sub-images, each represented with proportional frequency resolution. Finer level coefficients are estimated using wavelet transform.

In this method smoothing effect is reduced as high frequency components are added.

The zoomed images are more sharper and less blocky. The performance can be measured by calculating peak signal to noise ratio(PSNR)& Mean Square Error(MSE) .It is observed that this method gives much better PSNR & MSE compared to other methods.

Keywords
wavelet, multiresolution, zooming and zerotree.

1. INTRODUCTION
Due to the development of modern digital signal processing, image processing is becoming more and more important in our life. Digital zooming is encountered in many real applications such as electronic publishing, image database, digital camera, visible wireless telephone, medical imaging and so on. In order to have images with finer details for users, images often need to be zoomed in and out or reproduced to higher resolution from lower resolution. One common way for image zooming is interpolating the discrete source image. Interpolation is the first step of two basic re-sampling steps and turns a discrete image into a continuous function, which is necessary for various geometric transform of discrete images. There are various kinds of interpolation methods: linear, non-linear . The simplest and most popular approximations are related to pixel replication, bilinear inter-polation and bicubic interpolation methods. They have been routinely implemented in commercial digital image processing softwares. Pixel replication method is a technique of nearest neighbor interpolation, which is simple to implement by replicating the original pixels. This method is usually susceptible to the undesirable defect of blocking effects. Bilinear and bicubic interpolation employ first-order spline and second-order spline models, respectively. By doing so, more pleasing outcome is resulted for many real digital images.

A generic zooming algorithm takes as input an image and provides as output a picture of greater size preserving the information content of the original image as much as possible. Unfortunately, the methods mentioned in the passage above, can preserve the low frequency content of the source image well, but are not equally well to enhance high frequencies in order to produce an image whose visual sharpness matches the quality of the original one. Especially, when the image is zoomed by a large factor, the zoomed image looks very often blocky .

2. LITERATURE REVIEW
Image interpolation or zooming or generation of higher resolution image is one of the important branch of image processing. Much work is being done in this regard.

Researchers have proposed different solution for the interpolation problem. Schultz and Stevenson proposed a Bayesian approach for zooming[2]. In this approach ,the output image contains ripples.

In the super-resolution domain, Deepu and Choudhuri propose physics based approach[3].

Knox Carey et al. proposed wavelet based approach[4]. The visual results of this reduced-computation interpolation method are largely similar to those of the more computationally intensive method, but some edges are slightly smeared.

Jensen and Alastassiou proposed the non linear method for image zooming.

Parker, Kenyon, and Troxel published the first paper entitled "Comparison of Interpolation Methods" followed by a similar study presented by Maeland in. According to the above references, classical methods include linear interpolation and pixel replication. Linear interpolation tries to fit straight line between two lines. This technique leads to blurred image. Pixel replication copies neighbouring pixel to the empty location. This technique tends to produce blocky images.[5] Approaches like Spline and Sinc interpolation are reduced to these two extremities.

Blurred images are produced by interpolation process. A wavelet-based magnification method is proposed that both increases the resolution of an image and adds local high-frequency information’s, in order to provide digitally zoomed images with sharp edges. Wavelet transforms computed by the decimated Mallat's algorithm present pyramidal aspect[6]. This pyramidal analysis combined with a prediction of high-frequency coefficients is used to produce a magnified image. The prediction is based on a zero-crossings representation and on the construction of a multiscale edge-signature database. Performances are evaluated for synthetic and noisy images. A significant improvement regarding some classical methods (spline interpolation) is observed.

3. PROPOSED METHOD

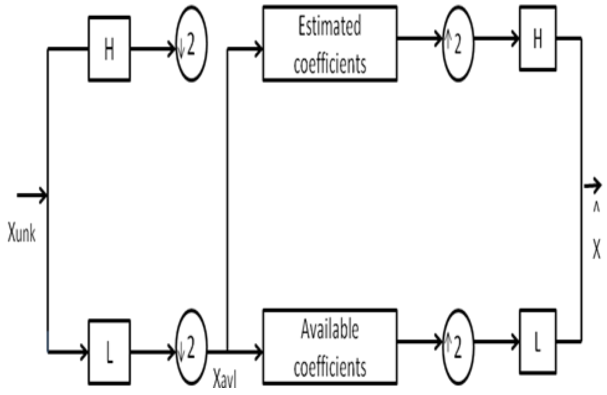

Figure 1. Proposed method for image zooming wavlet transform.

3.1 Block Diagram Description

In block diagram Xunk is (unknown) high resolution image where Xavl available low resolution image. H and L is appropriate high pass and low pass filter in wavelet analysis. Using Xavl, we estimate the coefficient required for synthesizing high resolution images. Having estimatimated the coefficients, rest is a standard wavelet synthesis filter bank.

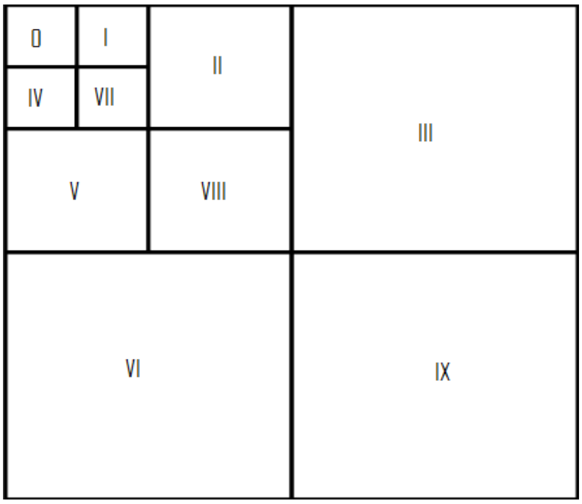

Figure 2. Estimation of coefficients.

To illustrate the estimation of coefficients consider the figure. We assume that wavelet transform of an M*M image composed of boxes 0 ,I,II,IV,V,VII,VIII is available & we want to zoom it to size 2M*2M.This would be possible if we can estimate wavelet coefficients in boxes III,VI,IX. Having estimated these wavelet coefficient ,we simply feed these along with M*M image the wavelet based image synthesis filter bankn& obtain the interpolated (zoomed)img of size 2M*2M. We exploit ideas from zero tree concept to estimate wavelet coefficient in boxes III,VI &IX.

To estimate these coefficients we use zero tree concept. It has following properties:

If a wavelet coefficient at a coarser scale is insignificant with respect to a given threshold T,then all wavelet coefficients of same orientation in same spatial location at finer scales are likely to be insignificant with respect to that T.

In a multiresolution system ,every coefficient at a given scale can be related to a set of coefficients at the next coarser scale of similar orientation.

3.2 Estimation of wavelet coefficient

Consider box I & II of Fig.2 coefficient d1(i1,j1) € I and d2(i2,j2) € II. Note that i1,j1 satisfy M/4<=i1<=(M/2)-1 and 0<=j1<=(M/4)-1. Also, i1 and i2 related by i1= [i2/2](where [.]represents floor operator); j1 and j2 are similarly related. The ratio of coefficient of finer scale(box II) and next coarser scale (box I) remains almost invariant. We define D(.)(i,j) as (between box I and box II):

$$D_1(i,j) = \frac{d_2(i,j)}{d_1\left(\left[\frac{i}{2}\right],\left[\frac{j}{2}\right]\right)} \qquad (1)$$

$$D_2(i,j) = \frac{d_2(i,j+1)}{d_1\left(\left[\frac{i}{2}\right],\left[\frac{j+1}{2}\right]\right)} \qquad (2)$$

These D(.)(i,j) values are used to estimate coefficients of dˆ at the finer scale (box III).

dˆ (2i,2j)=D1(i,j)d2(i,j)(1-ld(i.j))

dˆ(2i,2j+2)=D1(i,j)d2(i,j+1)(1-ld(i.j+1))
(3)

We set:

dˆ (2i,2j+1)= dˆ (2i,2j)

dˆ (2i,2j+3)= dˆ (2i,2j+2)
(4)

ld(i,j) is an indicator function ; ld(i,j) is set to zero ,if d(i,j) is significant, else to one. We define d(i,j) to be significant if |d(i,j)| >T. Note that Eq 3 implies an exponential decay . Now, the estimated dˆs and original M×M image is fed to wavelet based image synthesizer to obtained zoomed image.

3.3 Multi-resolution analysis

Multi-resolution analysis as implied by its name, analyzes the signal at different frequencies with different resolutions. Every spectral component is not resolved equally as was the case in the STFT.

MRA is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. This approach makes sense especially when the signal at hand has high frequency components for short durations and low frequency components for long durations. Fortunately, the signals that are encountered in practical applications are often of this type.

A multiresolution representation provides a simple hierarchical framework for interpreting the image information. At different resolutions, the details of an image generally characterize different physical structures of the scene. At a coarse resolution, these details correspond to the larger structures which provide the image “context”. It is therefore natural to analyze first the image details at a coarse resolution and then gradually increase the resolution.

3.4 Zero tree Concept

In a hierarchical subband system, which we have already discussed in the previous lessons, every coefficient at a given scale can be related to a set of coefficients at the next finer scale of similar orientation. Only, the highest frequency subbands are exceptions, since there is no existence of finer scale beyond these. The coefficient at the coarser scale is called the parent and the coefficients at the next finer scale in similar orientation and same spatial location are the children. For a given parent, the set of all coefficients at all finer scales in similar orientation and spatial locations are called descendants. Similarly, for a given child, the set of coefficients at all coarser scales of similar orientation and same spatial location are called ancestors. [8]

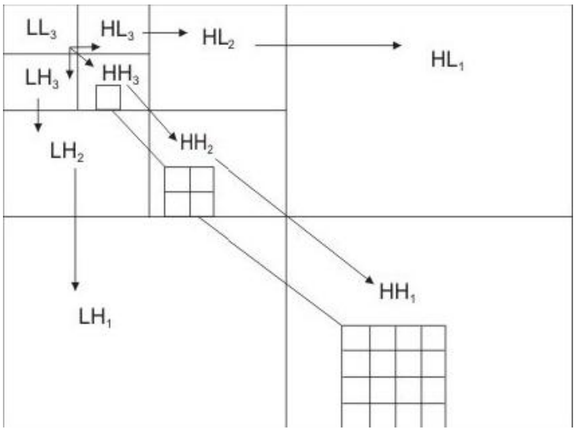

Figure 1. Parent-child dependencies of sub bands

Fig.3 illustrates this concept, showing the descendants of a DWT coefficient existing in HH3 subband. Note that the coefficient under consideration has four children in HH2 subband, since HH2 subband has four times resolution as that of HH3. Likewise, the coefficient under consideration in HH3 subband has sixteen descendants in subband HH1, which in this case is a highest-resolution subband. For a coefficient in the LL subband, that exists only at the coarsest scale (in this case, the LL3), the hierarchical concept is slightly different. There, a coefficient in LL3 has three children – one in HL3, one in LH3 and one in HH3, all at the same spatial location. Thus, every coefficient at any subband other than LL3 must have its ultimate ancestor residing in the LL3 subband.

The relationship defined above best depicts the concept of space-frequency localization of wavelet transforms. If we form a descendant tree, starting with a coefficient in LL3 as a root node, the tree would span all coefficients at all higher frequency subbands at the same spatial location.

3.5 Algorithm

1. Read the image
2. Take 2 level wavelet transform of image (x of size M×M)
3. Find the maximum coefficient in HH II
4. t=max/2
5. take the significant pixel and estimate the coefficients for HL III
6. repeat for LH III and HH III
7. take 3 level inverse wavelet transform of image(x)
8. postprocessing is done on the recovered image.

3.6 Performance Parameters

3.6.1 MEAN SQUARE ERROR

Mean square error is measure of the error between the original image and the zoomed image. It can be calculated by the formula given as:

$$MSE(X,X')=[1/N1*N2] \sum \sum [X(i,j)- X'(i,j)]^2 \quad (5)$$

Where,

X=original image of size N1×N2

X'=zoomed image

Mean square error should be as low as possible.

3.6.2 PEAK SIGNAL TO NOISE RATIO

This ratio is often used as a quality measurement between the original and a zoomed image. The higher the PSNR, the better the quality of the zoomed image.

$$PSNR = 10\log [255^2/MSE] \quad (6)$$

4. SIMULATION RESULTND DISCUSSION

Here we have taken image of cameraman(128x128),and observed output of proposed method.The experimental result is as shown below

Figure 4.1(a) Cameraman Original Image

Figure 4.1(b) Cameraman Zooming Image

Figure 4.2 (a) Lena Original Image

Figure 4.2(b) Lena Zooming Image

Here we have taken an gray image of lena (128×128). From the above two images it can observe that all image details are very clearly seen. Also, it has less artifacts .Image is not blur. Her hairs details are finely zoomed.

Fig.4.1(a)& Fig 4.2(a) shows input image & Fig.4.1(b)& Fig 4.2 (b) is ouput image. As seen in Fig.4.1(b) & Fig 4.2(b) image is better resolved and showing finer details .

Table 1 Perfromance parameter for Balck &White Image

Sr. No.	Image name	Wavelet used	MSE	PSNR
1	cameraman	haar	25.90	33.99
		db4	47.14	31.39
2	Lena	haar	42.36	31.86
		db4	69.96	29.68

Figure 4.3(a) Women Original Image (Colour)

Figure 4.3(b) Women Zooming Image (Colour)

The wrinkles on the face of the woman near the eyes and lips can be well observed in the above zoomed image. The edges of the columns of the building are also well zoomed.

Figure 4.4(a) Sat Original Image (Colour)

Figure 4.4(b) Sat Zooming Image (Colour)

Here we had taken satellite color image of size (128×128) as input. In zoomed image we can see that all details are retained.

Table 2 Performance Parameter for Colour Image

Sr.No.	Image Name	Wavelet used	MSE	PSNR
1	Sat_2	Haar	253.9371	24.0835
		db4	246.3714	24.2149
2	Woman	Haar	253.5000	24.0910
		db4	248.5294	24.1770

From above Table 1 & Table 2 it is seen that images are very well reconstructed by using wavelet. Also MSE and PSNR is improved considerably.

5. CONCLUSION

Experimental results shows that substantial improvement in Peak Signal to Noise Ratio and Mean Square Error. Zoomed image is more sharper and less blocky. As time complexity is more in proposed algorithm further optimized algorithms can be used.

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