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Digital Image Resizing Using Transform Domain Method

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***Abstract* — A simple interpolation-based approach for image resizing is proposed. The Interpolation-based approaches generally suffer from the problem of blurry and jagged edge. Therefore the resizing algorithm is designed to preserve the image content and to minimize the difference between the original image & the resized image. The proposed resizing algorithm can be used for integer as well as non-integer scale factors. It basically consists of 2 operations on the image - Sampling rate change and low pass filtering. The sampling rate change is done by bilinear interpolation. The anti-imaging low pass filter is implemented in 3 ways – 1) FIR low pass filter 2) Wavelet transform and 3) DCT.**

The performance of the algorithm is tested for 20 different types of images using each method for different scale factors. The test image is scaled by a scaling factor *a* and a reverse transformation with scaling factor 1/*a* is carried out using the same method. The loss of information is measured using PSNR. The results of comparisons show that the DCT method outperforms the other two methods. The performance of the algorithm is excellent for the low contrast images.

***Keywords* — bilinear interpolation, biorthogonal spline wavelet, wavelet transform, DCT.**

I. Introduction

Image resizing or scaling (magnification or reduction) is a common operation in image processing. It is a fundamental & extremely important type of image manipulation. It is required on a routine basis in digital photography, multimedia, and electronic publishing for generating preview images, or posting digital pictures on the Web.

The fastest, simplest and most commonly used image resizing methods are as follows.

The replication method is fast & simple but produces poor quality if factor of expansion is greater than 3. Bilinear interpolation attenuates frequencies near the cut off frequency, resulting in image blurring & smoothing. Quadratic or cubic interpolations can produce better results but still generates distortion near edges & in homogenous region. High resolution cubic splines & spline-like methods simulate the spline function & produce similar results to those of spline but use much simpler functions. Other methods are those based on image models such as Markov random fields, Gibbs random field. The recent methods are image resizing using DCT, neural networks & wavelets.

Image resizing and interpolation (e.g., for rotation) are two of the most useful image processing operations, and consequently there is a great amount of literature on the subject. However, many imaging professionals find the task of sorting out and implementing the most appropriate method quite challenging, due to the great number of possibilities, and of conflicting opinions. It is common to settle for some very simple approaches which were once meant to reduce complexity, or adopt one type that was shown to be excellent for one application, without knowing that it may be suboptimal for other applications.

Therefore such an approach should be used that is more convenient and easy to use, with less emphasis on computational complexity, and that yields high image quality. For that purpose simple interpolation-based approach for image resizing is proposed.

II. Theoretical Background

A. Decimation

Decimation can be regarded as the discrete-time counterpart of sampling. In sampling we start with a continuous-time signal $x(t)$ and convert it into a sequence of samples $x[n]$, whereas in decimation we start with a discrete-time signal $x[n]$ and convert it into another discrete-time signal $y[n]$, which consists of *sub-samples* of $x[n]$. Thus, the formal definition of M-fold decimation, or down-sampling, is defined by Equation 1. In decimation, the sampling rate is reduced from Fs to Fs/M by discarding $M - 1$ samples for every M samples in the original sequence.

$$y[n] = v[nm] = \sum_{-\infty}^{+\infty} h[k]x[nm-k] \qquad -(1)$$

The block diagram notation of the decimation process is depicted in Figure 1. An anti-aliasing digital filter precedes the down-sampler to prevent aliasing from occurring, due to the lower sampling rate.

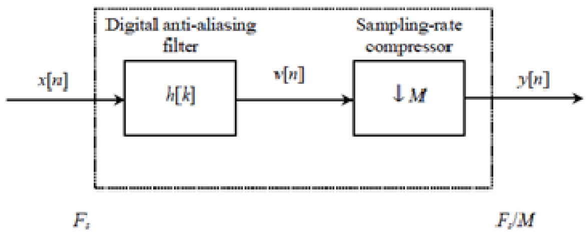

Fig.1. Block diagram notation of decimation, by a factor of M.

B. Interpolation

Interpolation is the exact opposite of decimation. It is an information preserving operation, in that all samples of $x[n]$ are present in the expanded signal $y[n]$. The mathematical definition of L-fold interpolation is defined by Equation 2 and the block diagram notation is depicted in fig. 2. Interpolation works by inserting (L–1) zero-valued samples for each input sample. The sampling rate therefore increases from Fs to LFs.

$$y[n] = L\sum_{-\infty}^{+\infty} h[k]w[n-k] \qquad -(2)$$

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Where, $w[n] = \begin{cases} x[n/L], & \text{if } n/L \text{ is non-integer} \\ 0, & \text{if } n/L \text{ is an integer} \end{cases}$

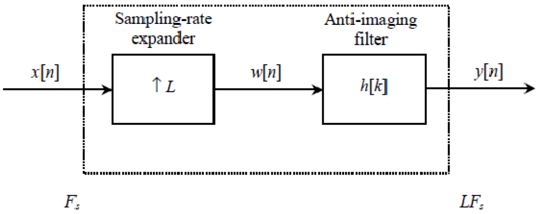

Fig.2. Block diagram notation of interpolation, by a factor of L.

C. The discrete cosine transform (DCT)

The discrete cosine transform (DCT) helps to separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete Fourier transform: it transforms a signal or image from the spatial domain to the frequency domain (Fig. 3).

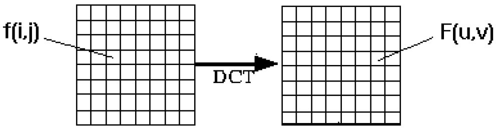

Fig.3. Discrete cosine transform

The One-Dimensional DCT:

The most common DCT definition of a 1-D sequence of length N is

$$c(u) = \alpha(u) \sum_{x=0}^{N-1} \left(f(x) \cos\left[\frac{\pi(2x+1)u}{2N}\right] \right) \quad -(3)$$

for $u = 0,1,2,\ldots,N-1$.

Similarly, the inverse transformation is defined as

$$f(x) = \sum_{u=0}^{N-1} \left(\alpha(u) c(u) \cos\left[\frac{\pi(2x+1)u}{2N}\right] \right) \quad -(4)$$

for $x = 0,1,2,\ldots,N-1$.

In both equations (3) and (4) $\alpha(u)$ is defined as,

$$\alpha(u) = \begin{cases} \sqrt{1/N}, & \text{for } u = 0 \\ \sqrt{2/N}, & \text{for } u \neq 0 \end{cases} \quad -(5)$$

It is clear from (3) that for $c(u=0) = \frac{1}{N}\sum_{x=0}^{N-1}(f(x))$, Thus, the first transform coefficient is the average value of the sample sequence. In literature, this value is referred to as the *DC Coefficient*. All other transform coefficients are called the *AC Coefficients.*

D. Discrete wavelet transform

The wavelet transform (WT) has gained widespread acceptance in signal processing and image compression. Because of their inherent multi-resolution nature, wavelets are especially suitable for applications where *scalability* and *tolerable degradation* are important. Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called *wavelets.* Wavelets are obtained from a single prototype wavelet *y(t)* called mother *wavelet* by *dilations* and *shifting:*

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad -(6)$$

where, a is the scaling parameter and b is the shifting parameter.

The 1-D wavelet transform is given by :

$$W_f(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt \quad -(7)$$

The inverse 1-D wavelet transform is given by:

$$x(t) = \frac{1}{C}\int_{0}^{\infty}\int_{-\infty}^{\infty} W_f(a,b)\psi_{a,b}(t)db\frac{da}{a^2} \quad -(8)$$

where, $C = \int_{-\infty}^{\infty}\frac{|\psi(\omega)|^2}{\omega}d\omega < \infty$

Discrete wavelet transform (DWT), which transforms a discrete time signal to a discrete wavelet representation. It converts an input series $x_0, x_1, ..x_m$, into one high-pass wavelet coefficient series and one low-pass wavelet coefficient series (of length n/2 each) given by:

$$H_i = \sum_{m=0}^{k-1} x_{2i-m} \cdot s_m(z) \quad -(9)$$

$$L_i = \sum_{m=0}^{k-1} x_{2i-m} \cdot t_m(z) \quad -(10)$$

where, $s_m(Z)$ and $t_m(Z)$ are called *wavelet filters*, K is the length of the filter, and i=0, ..., [n/2]-1. In practice, such transformation will be applied recursively on the low-pass series until the desired number of iterations is reached.

E. FIR filter

FIR filters are filters having a transfer function of a polynomial in *z*- and is an all-zero filter in the sense that the zeroes in the *z*-plane determine the frequency response magnitude characteristic. The *z* transform of a *N*-point FIR filter is given by

$$H(z) = \sum_{n=0}^{N-1} h(n)\, z^{-n} \quad -(11)$$

FIR filters are particularly useful for applications where exact linear phase response is required. The FIR filter is generally implemented in a non-recursive way which guarantees a stable filter.

A general FIR filter does not have a linear phase response but this property is satisfied when

$$h(n) = \pm h(M-1-n), \quad n = 0, 1, \ldots, M-1 \quad -(12)$$

III. Algorithm

To resize a digital image we typically perform 2 operations on the image - Sampling rate change and low pass filtering. To reduce an image to one half in each dimension, we first apply an anti-aliasing low pass filter then downsample by 2 in each dimension. To enlarge an image to 2 times in each dimension, we upsample by 2 in each dimension then apply an anti-imaging low pass filter for interpolation. The sampling rate change is done by bilinear interpolation. The anti-imaging low pass filter is implemented in 3 ways –

1) FIR low pass filter

2) Biorthogonal spline wavelet and

3) DCT.

A. Image resizing using FIR filter method

Image resizing can be done by integer or non-integer factors. For Image resizing by integer factor M>1, that is image enlargement, the image is first interpolated by M, then filtered by FIR filter with cut off frequency π/M.

For Image resizing by integer factor L<1, that is image reduction, the image is first filtered by FIR filter with cut off frequency π/L and then decimated by L.

For Image resizing by non-integer factor M/L the above two schemes are combined. The image size is increased by M and reduced by L. The image is first interpolated by M and filtered by FIR filter with cut off frequency min of π/M and π/L. The filtered image is then decimated by factor L.

The FIR filter is designed using rectangular window of length 7.

B. Image resizing using DWT and DCT method

For Image resizing by integer factor L<1, the image is first decomposed by Discrete wavelet transform or Discrete cosine transform. The π/L coefficients are taken and remaining coefficients are made zero. Then reverse transformation is carried out that is IDWT or IDCT. Then decimation by L is carried out to get the resized image.

For Image resizing by integer factor L<1, the image is first decomposed by Discrete wavelet transform or Discrete cosine transform. The π/L coefficients are taken and remaining coefficients are made zero. Then reverse transformation is carried out that is IDWT or IDCT. Then decimation by L is carried out to get the resized image.

For Image resizing by non-integer factor M/L, above two schemes are combined. The image is first interpolated by M and then it is decomposed by Discrete wavelet transform or Discrete cosine transform. The min of π/M and π/L coefficients are taken and remaining coefficients are made zero. The reverse transformation is carried out that is IDWT or IDCT. Then decimation by L is carried out to get the resized image.

IV. RESULTS

The test image is scaled by a scaling factor *a* and a reverse transformation with scaling factor 1/*a* is carried out using the same method. Figure 4 through 9 shows this result, using the 3 methods, for different scale factors. The loss of information is measured using PSNR.

A. Scale factor 2

Fig.4. FIR method PSNR= 30.37 db

Fig.5. Wavelet method PSNR= 30.20 db

Fig. 6 DCT method PSNR= 34.24db

B. Scale factor 3/4

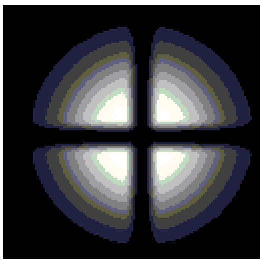

Fig.7. FIR filter method PSNR= 42.52 db

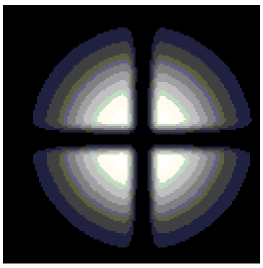

Fig.8. wavelet method PSNR= 46.81db

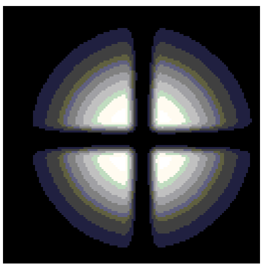

Fig.9. DCT method PSNR= 54.49 db

Fig. 10 through 12 illustrates PSNR comparison for 5 different images and scale factor using the 3 methods.

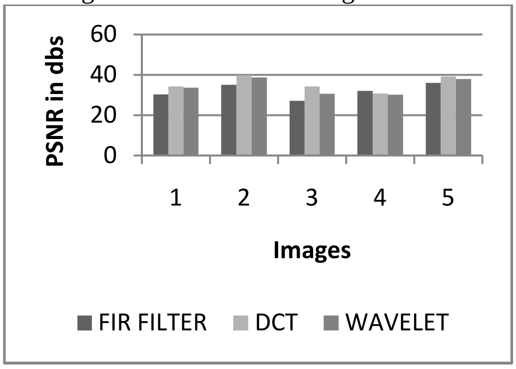

Fig.10. Graph for PSNR comparison for scale factor 2

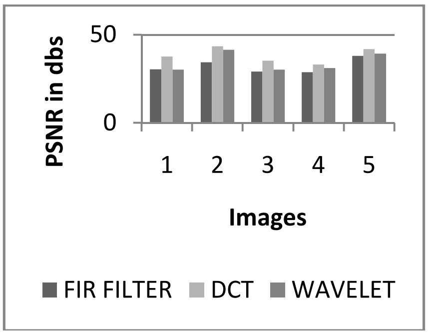

Fig.11. Graph for PSNR comparison for scale factor 4

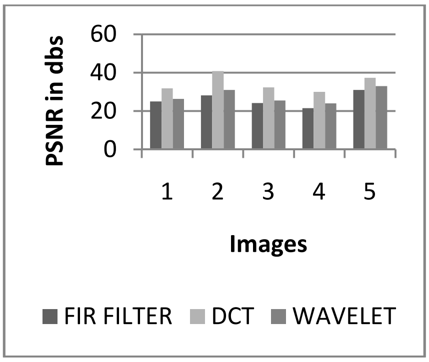

Fig.12. Graph for PSNR comparison for scale factor 3/4

V. Conclusion

The PSNR comparison for the three methods that is FIR filter, DCT and Biorthogonal Spline wavelet for different images and scale factors shows that the DCT method outperforms the other two methods. The performance of the algorithm is excellent for the low contrast images. While it degrades for high contrast images. The results of FIR method for high contrast images are better than the other two methods.

The performance of the algorithm increases with the scale factor(3/4 to 4). The performance is best for scale factor 4.

The range of PSNR for DCT method is 19 to 56 db, for wavelet method it is 17 to 55 db and for FIR method 19 to 52 db. For low contrast image DCT method gives PSNR in the range 49 to 56 db, wavelet method 42 to 55 db and FIR method 39 to 52 db.

It can be concluded from the comparisons of the performances of the algorithm that the proposed algorithm is suitable for low contrast images which has gradual change in their intensity values. The transform domain methods, that is, DCT and Wavelet give very good performance because the filtering is better in transform domain as the signal is separated in spectral bands.

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