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Wavelet Transform in Image Processing : Denoising, Segmentation and Compression of Digital Images

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ABSTRACT

Wavelet transform is a one of the most powerful concept used in image processing. Wavelet transform can divide a given function into different scale components and can find out frequency information without losing temporal information. Wavelet Transform is more suitable technique as compared to fourier transform because it is not possible with fourier transform to observe varying frequencies with time. Image processing is simply a processing of images or digital images in which processing is a collection of number of steps like denoising, segmentation, compression, representation and recognition. This paper will introduce basic concept of wavelet transform and use of wavelet transform in image denoising, image segmentation and image compression.

Keywords: Wavelet Transform, Multiresolution, Compression, Denoising.

I. INTRODUCTION

Wavelets are simply mathematical functions and these functions analyze data according to scale or resolution. They aid in studying a signal at different resolutions or in different windows. Wavelet domain comes under non-data adaptive transform of transform domain [1]. Wavelet functions are distinguished from other transformations such as Fourier transform because they not only dissect signals into their component frequencies but also vary the scale at which the component frequencies are analyzed. A wavelet is, as the name might suggest, a little piece of a wave. The finite scale multi-resolution representation of a discrete function can be known as a discrete wavelet transforms (DWT).

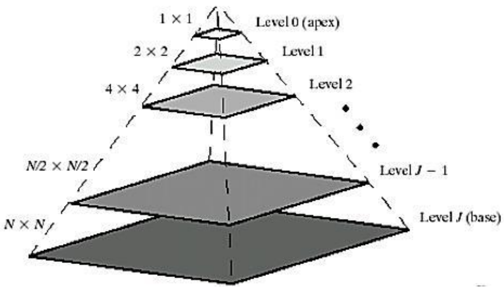

Figure 1. Image Pyramids

We can create multi-resolution pyramids of images which are given in figure 1. Wavelet is a more general way to represent and analyse multi-resolution images. As a result, wavelets are exceptionally suited for applications such as data compression, noise reduction, and singularity detection in signals. Discrete wavelet transform is a fast linear operation on a data vector, whose length is an integer power of 2 [2]. Discrete wavelet transform is invertible and orthogonal, where the inverse transform expressed as a matrix is the transpose of the transform matrix. The orthonormal basis or wavelet basis is defined as

$$\Psi_{(j,k)}(x) = 2^{j/2}\,\Psi(2^{j}x-k)$$

And the scaling function is given as

$$\Phi_{(j,k)}(x) = 2^{j/2}\,\Phi(2^{j}x-k)$$

Where is Ψ wavelet function and j and k are integers that scale and dilate the wavelet basis or function. The factor 'j' in the above equations is known as the scale index and it indicates the wavelet's width. The factor 'k' provides the position. The wavelet function is dilated by powers of two and it is translated by the integer *k*. In terms of the wavelet coefficients, the wavelet equation is

$$\Psi(x) = \sum_{k}^{n-1} g_k \sqrt{2\Phi(2x-k)}$$

Here g_0, g_1….. are high pass wavelet coefficients. These Wavelet coefficients calculated by a wavelet transform represent change in the time series at a particular resolution.

II. Wavelet Transform In Image Denoising

Image noise is the random variation of brightness or color information in images produced by the sensor and circuitry of a scanner or digital camera. The time series can be considered at various resolutions to filter out the noise. After applying wavelet transform small coefficients are dominated by noise, while coefficients with a large absolute value carry more signal information than noise. Replacing the smallest, noisy coefficients by zero and a backwards wavelet transform on the result may lead to a reconstruction with the essential signal characteristics and with less noise [3]. So, choosing of threshold level is important task. Those coefficients that have magnitude greater than threshold are considered as signal of interest and keep the same or modified according to type of threshold selected and other coefficients become zero. The image is reconstructed from the modified coefficients. This process is also known as the inverse discrete wavelets transform (IDWT) [4]. There exist various methods for wavelet thresholding, which rely on the choice of a threshold value. Some typically used methods for denoising image are Visu Shrink, Sure Shrink, Bayes Shrink, Neigh shrink, oracle Shrink, Smooth Shrink and Fuzzy based Shrink.

1) VisuShrink

It is a nonlinear wavelet domain filter introduced by Donoho . the threshold value 't' in this type is derived from the standard deviation of the noise[18]. It uses hard thresholding rule. It is also called as universal threshold and is defined as

$$t = \sigma\sqrt{2\log n}$$

σ^2 is the noise variance present in the signal and *n* *r*epresents the signal size or number of samples. The main drawback of Visushrink is it does not deal with minimizing the mean squared error . However, Visuhrink gives the images that are overly smoothed. This is because VisuShrink removes too many coefficients[18]. Another disadvantage is that it cannot remove speckle noise, which is multiplicative noise. It can only deal with an additive noise.

2) SureShrink

A Sureshrink wavelet domain filter threshold chooser based on Steins Unbiased Risk Estimator (SURE) was proposed by Donoho and Johnstone. It is determined from the both universal threshold and the SURE threshold [3,4]. It is subband dependent threshold, a threshold value for each resolution level in the wavelet transform which is referred to as level dependent thresholding. The main advantage of SureShrink is to minimize the mean squared error, unlike Visu Shrink, defined as

$$MSE = \frac{1}{n^2}\sum_{x,y=1}^{n}(z(x,y)-s(x,y))^2$$

Where z(x,y) is the estimate of the signal while s(x,y) is the original signal without noise And n is the size of the signal. The SureShrink threshold t_s is defined as

$$t_S = \min(t, \sigma\sqrt{2\log n})$$

where t denotes the value that minimizes Stein's Unbiased Risk Estimator,σ is the noise variance computed , and *n* is the size of the image.

3) BayeShrink

BayesShrink was proposed by Chang, Yu and Vetterli The goal of this method is to minimize the Bayesian risk, and hence its name, BayesShrink. It uses soft thresholding and it is also subband-dependent, like Sure Shrink, which means that threshold level is selected at each band of resolution in the wavelet decomposition [5]. The Bayes threshold t_b , is defined as

$$t_b = \frac{\sigma^2}{\sigma_s}$$

Where σ^2 is the noise variance and σ_s^2 is the signal variance without noise.

III. Wavelet Transform In Image Compression

Image compression addresses the problem of reducing the amount of data required to represent a digital image [5,6]. It is a process intended to yield a compact representation of an image, thereby reducing the image storage/transmission requirements. Compression is achieved by the removal of one or more of the three basic data redundancies i.e Coding redundancy, Interpixel redundancy and Psychovisual redundancy.

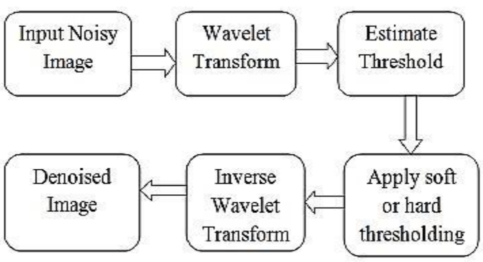

Figure 2. Basic Steps in image compression system

The main drawback of the DWT is that the wavelet coefficients are real numbers. In this case efficient lossless coding is not possible using linear transforms. The lifting scheme (LS) presented by Sweldens allows an efficient implementation of the DWT. Another of its properties is that perfect reconstruction is ensured by the structure of the LS itself. This allows new transformations to be used. One such transformation is the Integer wavelet transform (IWT) [7] it is a basic modification of linear transforms, where each filter output is rounded to the nearest integer. IWT can be used to have a unified lossy and lossless codec. It is also of interest for hardware implementations, where the use of floating point is still a costly operation.

The wavelet Lifting Scheme is a method for decomposing wavelet transforms into a set of stages. The convolution-based 1-D DWT requires both a large number of arithmetic computations and a large memory for storage. Such features are not desirable for either high speed or low power image processing applications. The main feature of the lifting-based wavelet transform is to break-up the high pass and the low pass wavelet filters into a sequence of smaller filters [8]. The lifting scheme requires fewer computations compared to the convolution-based DWT. Therefore the computational complexity is reduced to almost a half of those needed with a convolution approach. The main advantages of lifting scheme are as follows:

- It allows a faster implementation of the wavelet transforms.
- The lifting scheme allows a fully in-place calculation of the wavelet transform. In other words, no auxiliary memory is needed and the original signal (image) can be replaced with its wavelet transform.
- With the lifting scheme, the inverse wavelet transform can immediately be found by undoing the operations of the forward transform. In practice, this comes down to simply reversing the order of the operations and changing each + into a - and vice versa.

Because of the superior energy compaction properties and correspondence with human visual system, wavelet compression methods have produced superior objective and subjective results. Since wavelet basis consists of functions with both short support (for high frequencies) and long support (for low frequencies), large smooth areas of an image may be represented with very few bits, and details are added where it is needed.

IV. Wavelet Transform In Image Segmentation

Image segmentation has been an area of active research for the past two decades resulting in several image segmentation techniques have been described in the image processing research literature. This rapid increase is in part due to the fact that there exist several problem domains and applications that need to process and interpret image data in a domain specific manner [9]. Moreover, depending on the problem domain or application, there are several types of images that could be processed and analyzed such as, light intensity (grayscale), color, range (depth), thermal (infrared), sonar, X ray (radiographic), nuclear magnetic resonance images (MRI), and so on. This paper describes the technique of wavelet transform use for features extraction associated with individual image pixels. For the image decomposition and feature extraction the Haar transform has been applied as a basic tool used in the wavelet transform. Following subsections describe algorithms of image segmentation using wavelet transform.

1) Image Features Extraction

Texture is characterized by the spatial distribution of gray levels in a neighbourhood. An image region has a constant texture if a set of its local properties in that region is constant, slowly changing or approximately periodic. Texture analysis is one of the most important techniques used in analysis. There are three primary issues in texture analysis: classification, segmentation and shape recovery from texture. Analysis of texture [9] requires the identification of proper attributes or features that differentiate the textures of the image. In this paper, texture segmentation is carried out by comparing co-occurrence matrix features Contrast and Energy of size $N \times N$ derived from discrete wavelet transform overlapping but adjacent subimages $\mathbf{C}_{\mathbf{i},\mathbf{j}}$ of size 4×4, both horizontally and vertically. The algorithm of image features extraction involves

- decomposition, using one level DWT with the Haar transform, of each subimage **Ci**,**j** of size 4 × 4 taken from the top left corner
- computation of the co-occurrence matrix features energy and contrast given in Eqs (1) and (2) from the detail coefficients, obtained from each subimage **Ci**,**j**
- forming new feature matrices.

$$Energy = \sum_{i,j=1}^{N} C^2 i, j \quad (1)$$

$$Contrast = \sum_{i,j=1}^{N} (i-j)^2 Ci, j \quad (2)$$

2) Pixel Differences

After the computation of co-occurrence matrix features, a new matrix with differences is obtained. It is carrying out by calculation the difference between the value by value of features both in horizontal and vertical directions [10]. Then the segmentation band is formed across the texture boundaries.

3) Circular Averaging Filtering

In the image with the segmented band obtained after differences could appear artifacts or spurious spots. When within the same region the high differences of features values appeared, the spots and noise were formed. These spurious elements were removed by applying a circular averaging filter. First the filter with suitable radius was created and then applied for a segmented image to minimize and efface the image.

4) Thresholding and Skeletonizing

The processed image is then thresholded using global image threshold using Otsu's method [11] and black and white image is obtained. Because of the thick boundaries we must thin them on the line of one pixel thickness. To process this specific morphology operations were used. At first operation 'clean' removes isolated pixels - individual 1's that are surrounded by 0's. The second operation 'skel' removes pixels on the boundaries of objects but does not allow objects to break apart. The pixels remaining make up the image skeleton.

V. CONCLUSION

The technique of wavelet is computationally faster and gives better results in case of denoising, segmentation and compression. Some aspects that were analyzed in this paper may be useful for other denoising schemes, objective criteria for evaluating noise suppression performance of different significance measures. Segmentation using wavelet is also give better results as compared to traditional techniques. A new threshold function which is better as compare to other threshold function can be developed. Some function gives better edge perseverance, background information, contrast stretching, in spatial domain. In image compression high compression ration can be achieved with very low degradation in image quality

VI.REFERENCES

[1] Donoho.D.L,Johnstone.I.M, "Ideal spatial adaptation via wavelet shrinkage", Biometrika,81,pp.425-455,1994.

[2] Eric J. Stollnitz, Tony D. Derose and David H. Salesin, *Wavelets for Computer Graphics- Theory and Applications Book*, Morgan Kaufmann Publishers, Inc. San Francisco, California.

[3] Chang, S. G., Yu, B., and Vetterli, M. (2000). Adaptive wavelet thresholding for image denoising and compression. IEEE Trans. On Image Proc., 9, 1532–1546.

[4] H. A. Chipman, E. D. Kolaczyk, and R. E. McCulloch: „Adaptive Bayesian wavelet shrinkage", J. Amer. Stat. Assoc., Vol. 92, No 440, Dec. 1997, pp. 1413-1421

[5] Thierry Blu, and Florian Luisier "The SURE-LET Approach to Image Denoising". IEEE Transactions On Image Processing, VOL. 16, NO. 11, pp 2778 – 2786 , NOV 2007 .

[6] S. Bhavani, K. Thanushkodi, "A Survey on Coding Algorithms in Medical Image Compression", International Journal on Computer Science and Engineering, Vol. 02, No. 05, pp. 1429-1434, 2010.

[7] N. A. Koli, M. S. Ali, "A Survey on Fractal Image Compression Key Issues", Information Technology Journal, 2008.

[8] Othman Khalifa, "Wavelet Coding Design for Image Data Compression", The International Arab Journal of Information Technology, Vol. 6, No. 2, pp. 118-127, April 2009.

[9] E. Sharon, A. Brandt and R. Basri, "Fast Multi-Scale Image Segmentation," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, vol. 1, pp. 70-77, 2000.

[10] L. O. Donnell, C. F. Westin, W. E. L. Grimson, J. R. Alzola, M. E. Shenton and R. Kikinis, "Phase-Based user Steered Image Segmentation," *Proceedings of the Fourth International Conference on Medical Image Computing and Computer-Assisted Intervention*, pp. 1022-1030, 2001.

[11] B. Sumengen and B. S. Manjunath, "Graph Partitioning Active Contours for Image Segmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.28, no. 4, pp. 509-521, April 2006.