Analysis of Multispectral Image Using Discrete Wavelet Transform

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ABSTRACT:
In this paper we have analyzed the discrete wavelet transform of multispectral image of Bareilly region using MatLab tool. The wavelet transform is one of the most useful computational tools for a variety of signal and image processing applications. The wavelet transform is used for the compression of digital image because smaller data are important for storing images using less memory and for transmitting images faster and more reliably. Wavelet transforms are useful for images to reduce unwanted noise and blurring. A discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. A key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and time domain information.

Keywords: Wavelet, Wavelet Transform, DWT, Compression Techniques

1.Introduction

Now a days, wavelet theorems are the most popular methods of image processing, denoising and compression. A wavelet is a wave-like oscillation with an amplitude that starts out at zero, increases, and then decreases back to zero. Generally, wavelets are purposefully crafted to have some specific properties that make them useful for signal processing. Wavelets can be combined, using a "revert, shift, multiply and sum" and other techniques called convolution, with portions of an unknown signal to extract information from the unknown signal. These are the foundation for representing images in various degrees of resolution.

All wavelet transforms may be considered forms of time-frequency representation for continuous-time (analog) signals and so are related to harmonic analysis.

Depending upon different parameters the wavelet transform is classified as such:

There are two basic types of wavelet transform. One type of wavelet transform is designed to be easily reversible (invertible); that means the original signal can be easily recovered after it has been transformed. This kind of wavelet transform is used for image compression and cleaning (noise and blur reduction). Typically, the wavelet transform of the image is first computed, the wavelet representation is then modified appropriately, and then the wavelet transform is reversed (inverted) to obtain a new image. The second type of wavelet transform is designed for signal analysis. In these cases, a modified form of the original signal is not needed and the wavelet transform need not be inverted (it can be done in principle, but requires a lot of computation time in comparison with the first type of wavelet transform). This step deals with techniques for reducing the storage required to save an image, or the bandwidth required to transmit it. Although storage technology has improved significantly over the past decade it is need to be compressed for better utilization of memory space. The main purpose of this paper is concerned to the reversible DWT.

The paper is organized as follows: In section 2, we discuss about discrete wavelet transform in detail; experimental and results are given in section 3; finally, we conclude the paper in section 4.

2. Discrete wavelet transform**:** It is computationally impossible to analyze an image using all wavelet coefficients, so one may wonder if it is sufficient to pick a discrete subset of the upper half plane to be able to reconstruct a image from the corresponding wavelet coefficients. The basic idea in the DWT for a one dimensional signal is the following. The same concept is applied for images. A signal is split into two parts, usually high frequencies and low frequencies components. The edge components of the signal are largely confined to the high frequency part and then again the low frequency part is split into two parts of high and low frequencies. This process is continued an arbitrary number of time. Furthermore, from these DWT coefficients, the original signal can be reconstructed. This reconstruction process is called the inverse DWT (IDWT). The DWT and IDWT can be mathematically stated as follows. Let

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$$H(\omega) = \sum_k h_k e^{-jk\omega},$$

$$\text{and } G(\omega) = \sum_k g_k e^{-jk\omega}.$$

be a lowpass and a highpass filter, respectively, which satisfy a certain condition for reconstruction. A signal, x[n] can be decomposed recursively as:

$$c_{j-1,k} = \sum_n h_{n-2k} c_{j,n}$$

$$d_{j-1,k} = \sum_n g_{n-2k} c_{j,n}$$

for j= J+1; J; :::; J0 where cJ+1;k = x[k], k 2 Z, J+1 is the high resolution level index, and J0 is the low resolution level index. The coefficients cJ0; k; dJ0; k; dJ0+1; k; :::; d J; k are called the DWT of signal x[n], where cJ0; k is the lowest resolution part of x[n] and dj, k are the details of x[n] at various bands of frequencies. Furthermore, the signal x[n] can be reconstructed from its DWT coefficients recursively.

$$c_{j,n} = \sum_k h_{n-2k} c_{j-1,k} + \sum_k g_{n-2k} d_{j-1,k}.$$

To ensure IDWT and DWT relationship, the following orthogonality condition on the filters H(w) and G(w) is needed:

$$|H(\omega)|^2 + |G(\omega)|^2 = 1.$$

An example of such H(w) and G(w) is given by,

$$H(\omega) = \frac{1}{2} + \frac{1}{2} e^{-j\omega}$$

$$G(\omega) = \frac{1}{2} - \frac{1}{2} e^{-j\omega}$$

This is also well known as harr transform. The below given block diagram is used to represent the DWT of two dimensional image.

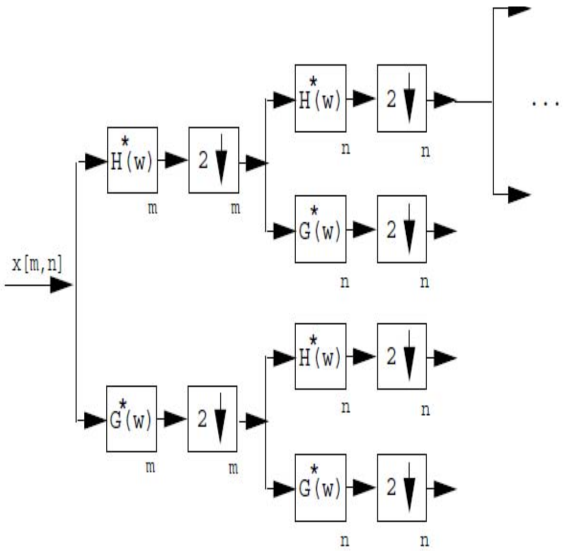

Fig1. DWT for two dimensional images

The above DWT and IDWT for a one dimensional signal x[n] can be also explained in the form of two channel tree-structured filter banks as shown in Fig. 2. The DWT and IDWT for two dimensional images x[m; n] can be similarly defined by implementing the one dimensional DWT and IDWT for each dimension m and n separately: DWTn [DWTm [x[m; n]]], which is shown in Fig.1. An image can be decomposed into a pyramid structure, shown in Fig.2,with various band information such as low-low frequency band, low-high frequency band, high-high frequency band etc. An example of such decomposition with two levels is shown in Fig. 3, where the edges appear in all bands except in the lowest frequency band, i.e., the corner part at the left and top.

The DWT results is explained from multi-resolution analysis, which involves the decomposition of an image in frequency channels of constant bandwidth on a logarithmic scale. It has advantages such as similarity of data structure with respect to the resolution and available decomposition at any level. It can be implemented as a multistage transformation. An image is decomposed into four subbands denoted LL, LH, HL, and HH at level 1 in the DWT domain, where LH, HL, and HH represent the finest scale wavelet coefficients and LL stands for the coarse-level coefficients. The LL subband can further be decomposed to obtain another level of decomposition. The decomposition process continues on the LL subband until the desired number of levels determined by the application is reached. The DWT does not actually provide a frequency representation of an image as mentioned earlier, but rather provides a joint time-scale representation of an image.

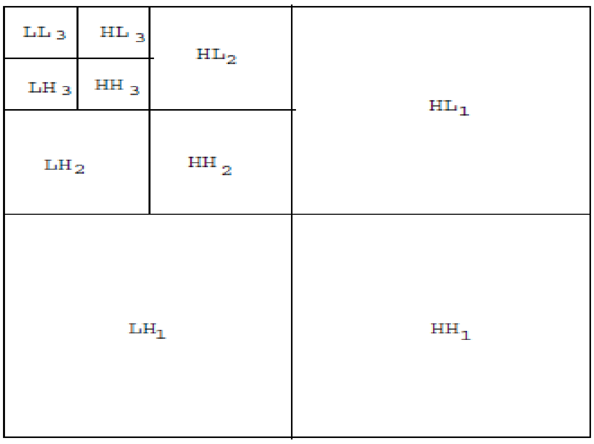

Fig2. DWT pyramid decomposition of an image

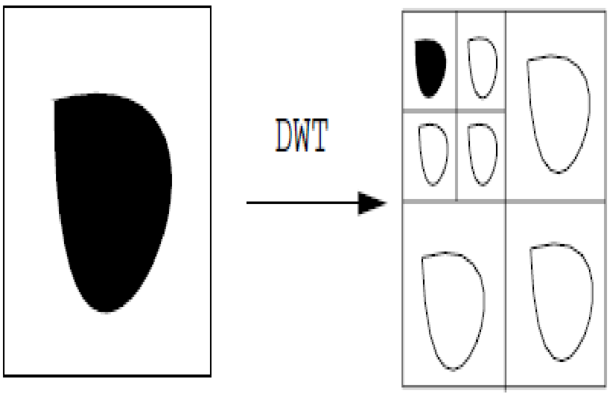

Fig3. Example of DWT pyramidal decomposition

3. Results and discussions:

Figure 4(a):Multispectral image of Bareilly region.

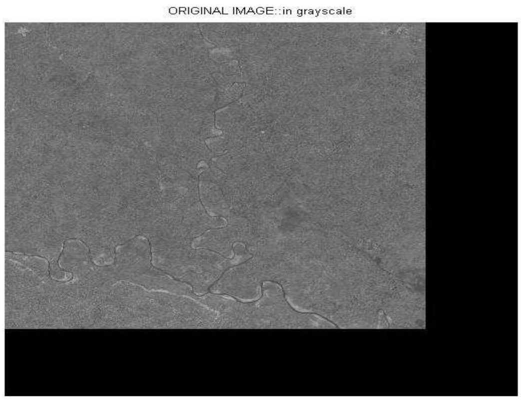

Figure 4(b): Grayscale image of Bareily region.

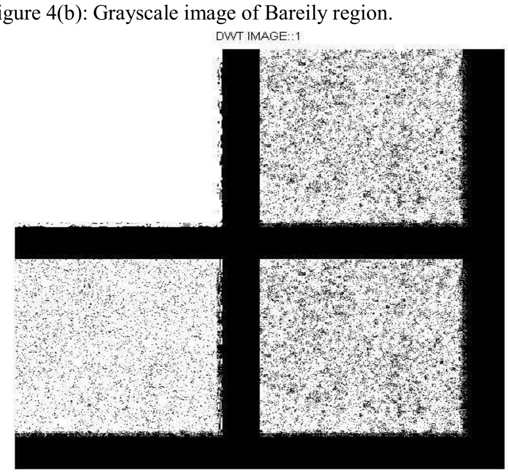

Figure 4(c): First Wavelet Transform of Grayscale image of Bareily region.

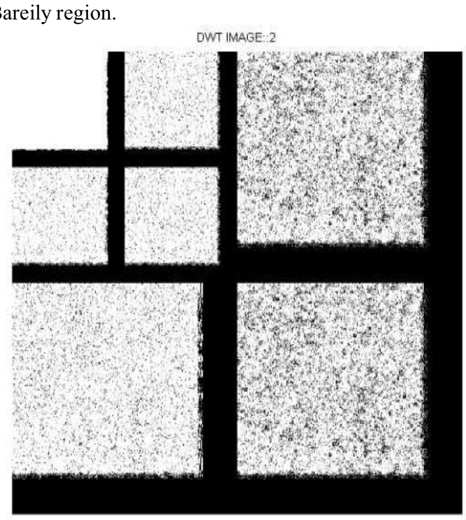

Figure 4(d): Second Wavelet Transform of Grayscale image of Bareily region.

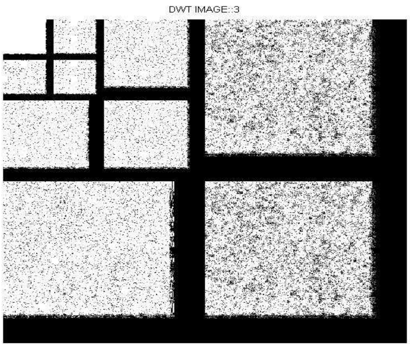

Figure 4(c): Third Wavelet Transform of Grayscale image of Bareily region.

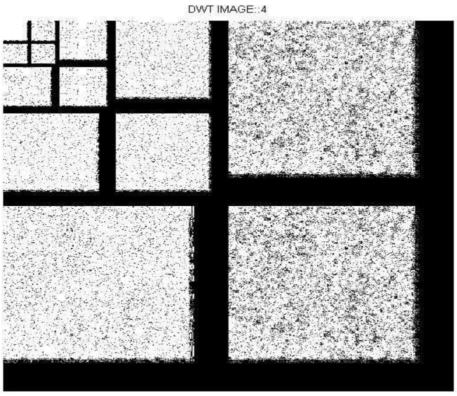

Figure 4(d): Fourth Wavelet Transform of Grayscale image of Bareily region.

In the above performed experiments in Matlab we find that till four wavelet transform can be applied to multispectral image since fifth wavelet coefficient becomes zero and don't give any information.

4. Conclusion:

An adaptive and efficient multiresolution algorithm for compression of digital image is performed. Among the transform domain compression techniques discrete wavelet transform (DWT) based compresssion techniques have gained more popularity because DWT has a number of advantages over other transform such as progressive and low bit-rate transmission, quality scalability and region-of-interest. Their success is supported on the fact that the wavelet transforms of images in which the most of the wavelet coefficients are close to zero. This implies that image approximations based on a small subset of wavelets are typically very accurate, which is a key to wavelet-based compression.

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