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Image Enhancement in Remote Sensing Application using Modified Dual Tree DWT

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***Abstract* – In this paper, Enhancement of image in remote sensing application using modified Dual tree DWT technique has been proposed. The technique decomposes the input image into the number of frequency sub bands by using DWT and estimates the values using many decomposition levels in sub-band image, and then, it reconstructs the enhanced image by applying inverse DWT. The technique is compared with conventional techniques such as standard wavelet transforms to enhance the image brightness and easy to find the objects present in it. The experimental results show the superiority of the proposed method over conventional method.**

***Keywords* - Discrete WT, Dual tree DWT, Multi Resolution.**

I. Introduction

A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. Wavelets can be combined, using a "revert, shift, multiply and sum" technique called convolution, with portions of an unknown signal to extract information from the unknown sigma. If this wavelet were to be convolved at periodic intervals with a signal created from the recording of a song, then the results of these convolutions would be useful for determining when the Middle C note was being played in the song. Mathematically, the wavelet will resonate if the unknown signal contains information of similar frequency - just as a tuning fork physically resonates with sound waves of its specific tuning frequency. This concept of resonance is at the core of many practical applications of wavelet theory.

As a mathematical tool, wavelets can be used to extract information from many different kinds of data, including - but certainly not limited to - audio signals and images. Sets of wavelets are generally needed to analyze data fully. A set of "complementary" wavelets will deconstruct data without gaps or overlap so that the deconstruction process is mathematically reversible. Thus, sets of complementary wavelets are useful in wavelet based compression/decompression algorithms where it is desirable to recover the original information with minimal loss.

In formal terms, this representation is a wavelet series representation of a square-integral function with respect to either a complete, orthonormal set of basic functions, or an over complete set or frame of a vector space, for the Hilbert space of square integral functions. The complex wavelet transform is a complex-valued extension to the standard discrete wavelet transform (DWT). It is a two-dimensional wavelet transform which provides sparse representation, and useful characterization of the structure of an image [1]. Further, it purveys a high degree of shift-invariance in its magnitude. However, a drawback to this transform is that it is exhibits 2^d (where d is the dimension of the signal being transformed) redundancy compared to a separable.

In the area of computer vision, by exploiting the concept of visual contexts, one can quickly focus on candidate regions, where objects of interest may be found, and then compute additional features through the CWT for those regions [2] only. These additional features, while not necessary for global regions, are useful in accurate detection and recognition of smaller objects. Similarly, the CWT may be applied to detect the activated voxels of cortex and additionally the temporal independent component analysis may be utilized to extract the underlying independent sources whose number is determined by Bayesian information criterion.

The Dual-Tree Complex Wavelet Transform (ℂWT) is nearly shift invariant and directionally selective in two and higher dimensions. The multidimensional dual-tree ℂWT is no separable but is based on a computationally efficient, separable filter bank.

II. Dual-Tree Complex Wavelet Transform

The Dual-tree complex wavelet transform (DTCWT) calculates the complex transform of a signal using two separate DWT decompositions (tree a and tree b). If the filters used in one are specifically designed different from those in the other it is possible for one DWT [3] to produce the real coefficients and the other the imaginary. This redundancy of two provides extra information for analysis but at the expense of extra computational power. It also provides approximate shift-invariance yet still allows perfect reconstruction of the signal.

The design of the filters is particularly important for the transform to occur correctly and the necessary characteristics are: The low-pass filters in the two trees must differ by half a sample period, Reconstruction filters [4] are the reverse of analysis, All filters from the same orthonormal set, Tree a filters are the reverse of tree b filters and Both trees have the same frequency response.

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III. Discrete Wavelet Transforms

It is computationally impossible to analyze a signal 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 signal from the corresponding wavelet coefficients. One such system is the affine system for some real parameters *a>1, b>0*. The corresponding discrete subset of the half fs plane consists of all the points $(a^m, na^m b)$ with integers $m, n \in z$.

The corresponding *baby wavelets* are now given as

$$\psi_{m,n}(t)=a^{-\frac{m}{2}}\psi\left(a^{-m}t-nb\right). \quad (3.1)$$

A sufficient condition for the reconstruction of any signal *x* of finite energy by the formula

$$x(t)=\sum_{m\in z}\sum_{n\in z}\langle x,\psi_{m,n}\rangle.\psi_{m,n}(t) \quad (3.2)$$

is that the functions $\{\psi_{m,n} : m, n \in z\}$ form a tight frame of $L^2(R)$.

A. Multi-resolution discrete wavelet transforms

In any discredited wavelet transform, there are only a finite number of wavelet coefficients for each bounded rectangular region in the upper half plane [5]-[9]. Still, each coefficient requires the evaluation of an integral. To avoid this numerical complexity, one needs one auxiliary function, the father wavelet $\phi \in L^2(R)$. Further, one has to restrict a to be an integer. A typical choice is a=2 and b=1.

From the mother and father wavelets one constructs the subspaces

$$V_m = span\left(\phi_{m,n} : n \in z\right) \quad (3.3)$$

where $\phi_{m,n}(t)=2^{-\frac{m}{2}}\phi\left(2^{-m}t-n\right)$

and $W_m = span\left(\psi_{m,n} : n \in z\right)$ (3.4)

where $\psi_{m,n}(t)=2^{-\frac{m}{2}}\psi\left(2^{-m}t-n\right)$

$$\{0\}\subset\ldots\subset V_1\subset V_0\subset V_{-1}\subset\ldots\subset L^2(R)$$

From these one requires that the sequence forms a multi-resolution analysis of $L^2(R)$ and that the subspaces $\ldots, W_1, W_0, W_{-1}, \ldots$ are the orthogonal "differences" of the above sequence, that is, W_m is the orthogonal complement of V_m inside the subspace $V_{m-\ldots1}$. In analogy to the sampling theorem[10]-[13] one may conclude that the space V_m with sampling distance 2^m more or less covers the frequency baseband from *0* to 2^{m-1}. As orthogonal complement, W_m roughly covers the band $\left[2^{-m-1}, 2^{-m}\right]$.

From those inclusions and orthogonality relations follows the existence of sequences

$$h=\{h_n\} n \in z \quad (3.5)$$

and $g=\{g_n\} n \in z$ (3.6)

that satisfy the identities $h_n = \langle \phi_{0,0}, \phi_{-1,n}\rangle$ (3.7)

and $\phi(t)=\sqrt{2}\sum_{n\in z} h_n\, \phi(2t-n)$ (3.8)

$$g_n = \langle \psi_{0,0}, \phi_{-1,n}\rangle \quad (3.9)$$

$$\psi(t)=\sqrt{2}\sum_{n\in z} g_n\, \phi(2t-n) \quad (3.10)$$

Multi-resolution is a general method for constructing orthonormal bases. We should note that even though most orthonormal wavelet [14][15] bases come from multi-resolution not all do. However, most "nice" ones do: for instance, all orthonormal bases with a compactly supported are known to come from multiresolution. Intuitively, multiresolution slices the space L2 into a nested sequence of subspaces Vi, where each Vi corresponds to a different scale. The multiresolution is completely determined by the choice of a special function, called the scaling function. The second identity of the first pair is a refinement equation [16]-[18] for the father wavelet. Both pairs of identities form the basis for the algorithm of the fast wavelet transform.

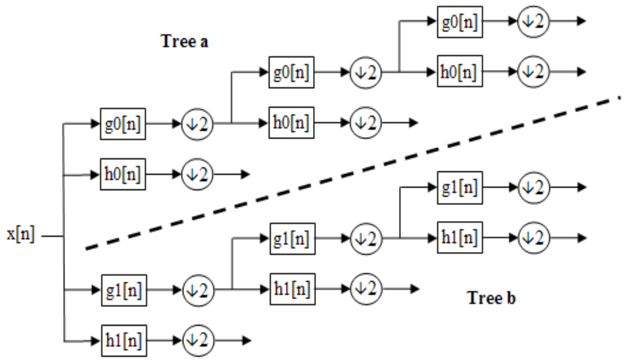

Fig.1. Dual Tree Discrete Wavelet Transform

IV. Experimental Results

Our proposed technique decomposes the input image into the four frequency sub bands by using DWT and estimates the singular value matrix of the low sub-band image, and then, it reconstructs the enhanced image by applying inverse DWT. The technique is compared with conventional images. As a ground truth for accuracy evaluation purposes we consider a high resolution version of these gray level images are used. The high resolution images were down sampled by a factor of 4 to create low resolution images. The process between input and reconstructed images are done by using many level of decomposition. The experimental results of the modified Dual tree DWT methods are shown in below. In this section, first the input image is given to our system.

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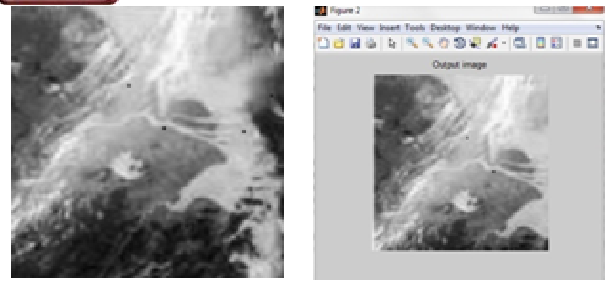

Fig.2. (a) & (b) Original Image and Output of modified Dual tree DWT method

The images are first decomposed into many levels such as horizontal, vertical and diagonal way to identify the objects easily. After decomposition the original image are reconstructed using dual tree discrete wave transform technique.

The input image is downsampled to reduce the sampling rate. To ensure that anti-aliasing filter is used to reduce the bandwidth of the signal before the signal is downsampled; the overall process is called Decimation. Note that if the original signal had been bandwidth limited, and then first sampled low-pass filtered at a rate higher than the Nyquist minimum, then the downsampled signal may already be Nyquist compliant, so the down sampling can be done directly without any additional filtering. Down sampling only changes the sample rate not the bandwidth of the signal. The only reason to filter the bandwidth is to avoid the case where the new sample rate would become lower than the Nyquist requirement and then cause the aliasing by being below the Nyquist minimum.

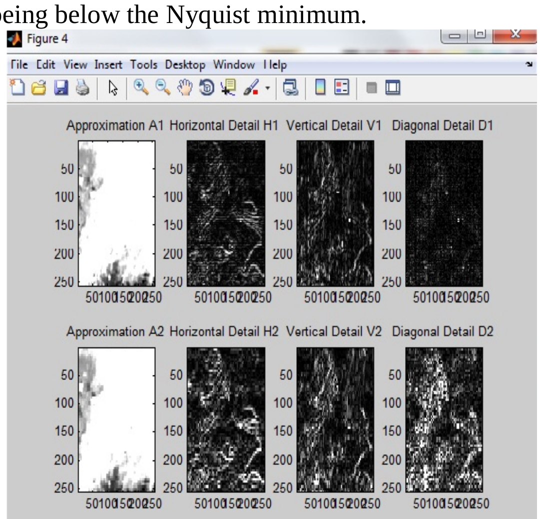

Fig.3. Results of First Level Decomposition

The first step calls for the use of a perfect low-pass filter, which is not implementable for real-time signals. When choosing a realizable low-pass filter this will have to be considered along with the aliasing effects it will have. Realizable low-pass filters have a "skirt", where the response diminishes from near unity to near zero. So in practice the cutoff frequency is placed far enough below the theoretical cutoff that the filter's skirt is contained below the theoretical cutoff.

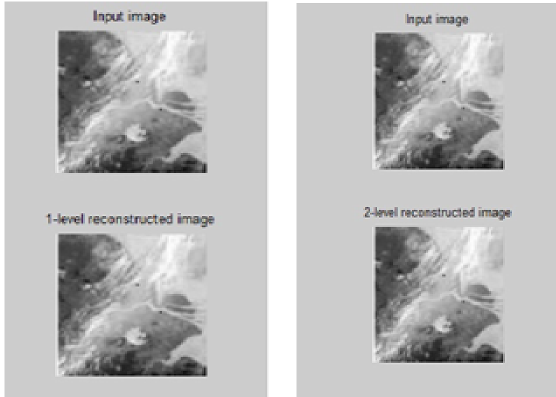

Fig.4. Input image, 1 & 2 Level Reconstructed Image

Then the images are decomposed into second level such as horizontal, vertical and diagonal for further enhancement to find out the objects clearly.

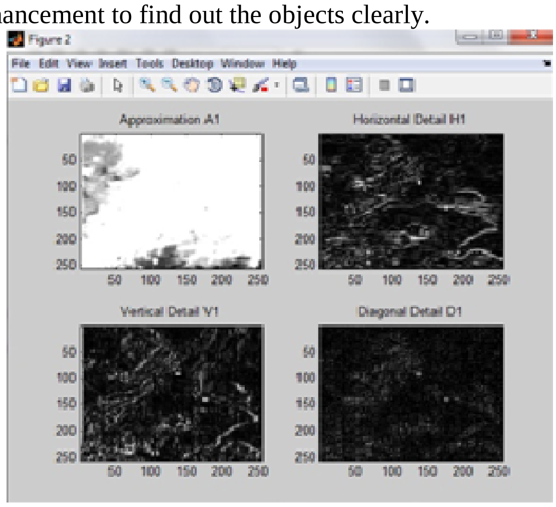

Fig.5. Results of Second Level Decomposition

V. Conclusion

This paper proposes an enhancement of satellite image using modified dual tree DWT technique. The proposed technique decomposed the input image into the DWT sub bands, and, after updating the singular value matrix of the Dual sub band, it reconstructed the image by using IDWT. The visual results on the final image quality show the superiority of the proposed method over the conventional method. We have designed a technique for efficiently decomposing the images into many levels in applications. Our experiment shows that the proposed technique is more accurate than traditional DWT.

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