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An Improvement of PSNR by Wavelet based True Compression of SAR Images

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Abstract - In Image Compression, the main intend is to shrink the number of bits required to represent an image by removing the spatial and spectral redundancies. The discrete wavelet transform has emerged as a popular technique for image compression. The result of the compression ratio changes as per the basis and type of wavelet used. In this paper focused on the selection of mother wavelet on the basis of nature of images, improve the quality as well as compression ratio extremely. We suggest the new technique, which is based on co-efficient thresholding. This method reduces the time complexity of wavelet packets decomposition. Our algorithm selects the sub-bands, which include significant information based on threshold entropy. The improved encoding technique of Huffman coding is suggested provides better results than existing compression methods.

Index Terms – Image, Compression, Co-efficient thresholding Method (CTM), Sub band coding, Wavelet, Huffman coding, True Compression.

1 INTRODUCTION

Image compression plays an essential role in several important and diverse applications like videoconferencing, remote sensing, medical imaging etc.,[1] These requirements are not fulfilled with old techniques of compression like Fourier Transform, Hadamard and Cosine Transform etc. The wavelet transform approach serves the purpose very efficiently. The basic idea behind the image compression is that in most of the images we find that their neighboring pixel. In this paper, we proposed compression scheme based on wavelet transform, which involves a discrete wavelet transform (DWT) for an image followed by quantization process for the wavelet coefficients after using a suitable bits allocation scheme [2]. The wavelet transform is one of the most exciting developments in the signal-processing field during the past decades. This is especially true when it is utilized in compressing images [3,4]. It is a well-established technique to compress independently the components of colored images and it has attracted a great interest in the area of image compression because of its excellent localization in both spatial and frequency domains.

The goal of true compression is to minimize the number of bits needed to represent it, while storing information of acceptable quality. Wavelets contribute to effective solutions for this problem. The complete chain of compression includes iterative phases of quantization, coding, and decoding, in addition to the wavelet processing.[5] A measure of achieved compression is given by the compression ratio (CR) and the Bit-Per-Pixel (BPP) ratio[6]. CR and BPP represent equivalent information. CR indicates that the compressed image is stored using CR of the initial storage size while BPP is the number. The goal of true compression is to minimize the number of bits needed to represent it, while storing information of acceptable quality. Wavelets contribute to effective solutions for this problem. The complete chain of compression includes iterative phases of quantization, coding, and decoding, in addition to the wavelet processing.[5] A measure of achieved compression is given by the compression ratio (CR) and the Bit-Per-Pixel (BPP) ratio[6]. CR and BPP represent equivalent information. CR indicates that the compressed image is stored using CR of the initial storage size while BPP is the number of bits used to store one pixel of the image. For a grayscale image the initial BPP is 8. For a true color image the initial BPP is 24,because 8 bits are used to encode each of the three colors (RGB color space) [7].The challenge of compression methods is to find the best compromise between a low compression ratio and a good perceptual result. The wavelet decomposes the image, and generates four different horizontal frequencies and vertical frequencies outputs. These outputs are referred as approximation, horizontal detail, vertical detail, and diagonal detail. The approximation contains low frequency horizontal and vertical components of the image. The decomposition procedure is repeated on the approximation sub-band to generate the next level of the decomposition, and so on. It is leading to well known pyramidal decomposition tree. Wavelets with many vanishing yield sparse decomposition [8] of piece wise smooth surface; therefore they provide a very appropriate tool to compactly code smooth images.

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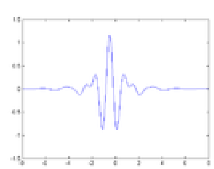
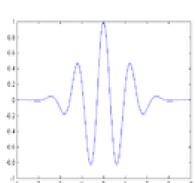
Further research has been done on still image compression and JPEG-2000 standard is established in 1992 and work on JPEG-2000 for coding of still images has been completed at end of year 2000. The JPEG 2000 standard employs wavelet for compression due to its merits in terms of scalability, localization and energy concentration [6, 7]. It also provides the user with many options to choose to achieve further compression. JPEG-2000 standard supports decomposition of all the sub bands at each level and hence requires full decomposition at a certain level. The compressed images look slightly washed-out, with less brilliant color. This problem appears to be worse in JPEG than in JPEG-2000 [9]. Both JPEG-2000 and JPEG operate in spectral domain, trying to represent the image as a sum of smooth oscillating waves. JPEG-2000 suffers from ringing and blurring artifacts. [9] The encoding phase of compression reduces the overall number of bits needed to represent the data set.

2. WAVELETS

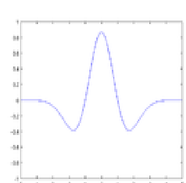
A wavelet is a wave-like oscillation with an amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. Wavelets can be combined, using a "shift, multiply and sum" technique called convolution [9], with portions of an unknown signal to extract information from the unknown signal. For example, a wavelet could be created to have a frequency of Middle C and a short duration of roughly a 32nd note. 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 [11]. This concept



Meyer



Morlet



Mexican Hat

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 [10,11].

Wavelet theory is applicable to several subjects. All wavelet transforms may be considered forms of time-frequency representation for continuous-time (analog) signals and so are related to harmonic analysis. Almost all practically useful discrete wavelet transforms use discrete-time filter banks. These filter banks are called the wavelet and scaling coefficients in wavelets nomenclature. These filter banks may contain either finite impulse response (FIR) or infinite impulse response (IIR) filters. The wavelets forming a continuous wavelet transform (CWT) [12] are subject to the uncertainty principle of Fourier analysis respective sampling theory: Given a signal with some event in it, one cannot assign simultaneously an exact time and frequency response scale to that event. The product of the uncertainties of time and frequency response scale has a lower bound. Thus, in the scale gram of a continuous wavelet transform of this signal, such an event marks an entire region in the time-scale plane, instead of just one point. Also, discrete wavelet bases may be considered in the context of other forms of the uncertainty principle. In continuous wavelet transforms, a given signal of finite energy is projected on a continuous family of frequency bands (or similar subspaces of the L^p function space $L^2(\mathbb{R})$). For instance the signal may be represented on every frequency band of the form [*f*,2*f*] for all positive frequencies *f*>*0*. Then, the original signal can be reconstructed by a suitable integration over all the resulting frequency components.

The frequency bands or subspaces (sub-bands) are scaled versions of a subspace at scale *1*. This subspace in turn is in most situations generated by the shifts of one generating function $\psi \in L^2(\mathbb{R})$, the *mother wavelet*. For the example of the scale one frequency band [1,2] this function is

$$\psi(t) = 2\,\mathrm{sinc}(2t) - \mathrm{sinc}(t) = \frac{\sin(2\pi t) - \sin(\pi t)}{\pi t}$$

with the (normalized) sinc function. Other example mother wavelets are:

The subspace of scale *a* or frequency band $[1/a,\ 2/a]$ is generated by the functions (sometimes called *child wavelets*)

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

where a is positive and defines the scale and b is any real number and defines the shift. The pair *(a,b)* defines a point in the right half plane $\mathbb{R}_+ \times \mathbb{R}$.

The projection of a function x onto the subspace of scale a then has the form

$$x_a(t) = \int_{\mathbb{R}} WT_\psi\{x\}(a,b)\cdot\psi_{a,b}(t)\,db$$

with *wavelet coefficients*

$$WT_\psi\{x\}(a,b) = \langle x, \psi_{a,b}\rangle = \int_{\mathbb{R}} x(t)\psi_{a,b}(t)\,dt.$$

For the analysis of the signal x, one can assemble the wavelet coefficients into a scaleogram of the signal.

2.1. Discrete wavelet transforms

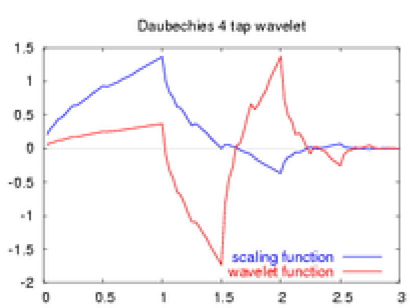
It is computationally impossible to analyze a signal using all wavelet coefficients, so one may wonder if it is sufficient to pick a discrete subset of the upper half plane to be able to reconstruct a signal from the corresponding wavelet coefficients. One such system is the affine system for some real parameters $a>1$, $b>0$. The corresponding discrete subset of the half plane consists of all the points $(a^m, n\,a^m b)$ with integers $m,n \in \mathbb{Z}$ The corresponding *baby wavelets* are now given as
$\psi_{m,n}(t) = a^{-m/2}\psi(a^{-m}t - nb)$.

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

$$x(t) = \sum_{m\in\mathbb{Z}}\sum_{n\in\mathbb{Z}}\langle x,\,\psi_{m,n}\rangle\cdot\psi_{m,n}(t)$$

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

2.2Multiresolution discrete wavelet transforms



D4 wavelet

In any discredited wavelet transform, there are only a finite number of wavelet coefficients for each bounded rectangular region in the upper half plane. Still, each coefficient requires the evaluation of an integral. To avoid this numerical complexity, one needs one auxiliary function, the *father wavelet* $\phi \in L^2(\mathbb{R})$ *[15]*. Further, one has to restrict a to be an integer. A typical choice is $a=2$ and $b=1$. The most famous pair of father and mother wavelets is the daubechies 4 tap wavelet.

From the mother and father wavelets one constructs the subspaces

$V_m = \operatorname{span}(\phi_{m,n} : n \in \mathbb{Z})$, where $\varphi_{m,n}(t) = 2^{-m/2}\varphi(2^{-m}t - n)$

and

$W_m = \operatorname{span}(\psi_{m,n} : n \in \mathbb{Z})$, where $\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n)$.

From these one requires that the sequence

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

forms a multiresolution analysis of $L^2(\mathbb{R})$ 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-1}. In analogy to the sampling theorem 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 $[2^{-m-1}, 2^{-m}]$.

From those inclusions and orthogonality relations follows the existence of sequences $h = \{h_n\}_{n\in\mathbb{Z}}$ and $g = \{g_n\}_{n\in\mathbb{Z}}$ that satisfy the identities

$h_n = \langle \phi_{0,0},\, \phi_{-1,n}\rangle$ and

$$\phi(t) = \sqrt{2}\sum_{n\in\mathbb{Z}} h_n\phi(2t-n)$$

and

$g_n = \langle \psi_{0,0},\, \phi_{-1,n}\rangle$ and

$$\psi(t) = \sqrt{2}\sum_{n\in\mathbb{Z}} g_n\phi(2t-n).$$

3. Wavelet and Wavelet Packet

In order to represent complex signals efficiently, a basis func-

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tion should be localized in both time and frequency domains. The wavelet function is localized in time domain as well as in frequency domain, and it is a function of variable parameters. The wavelet decomposes the image, and generates four different horizontal frequencies and vertical frequencies outputs. These outputs are referred as approximation, horizontal detail, vertical detail, and diagonal detail. The approximation contains low frequency horizontal and vertical components of the image. The decomposition procedure is repeated on the approximation sub-band to generate the next level of the decomposition, and so on. It is leading to well known pyramidal decomposition tree. Wavelets with many vanishing yield sparse decomposition of piecewise smooth surface; therefore they provide a very appropriate tool to compactly code smooth images. Wavelets however, are ill suited to represent oscillatory patterns [13, 14]. A special from a texture, oscillating variations, rapid variations in the intensity can only be described by the small-scale wavelet coefficients. Unfortunately, these small-scale coefficients carry very little energy, and are often quantized to zero even at high bit rate [16] up to third level.

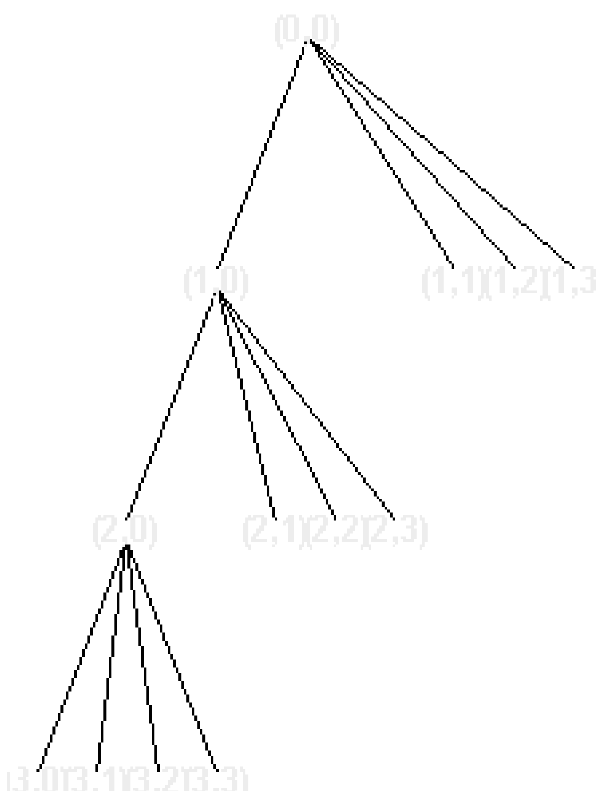

Figure 1. The-tree structure of wavelet decomposition

LL1LL2	LL1HL2	HL1LL2	HL1HL2
LL1LH2	LL1HH2	HL1LH2	HL1HH2
LH1LL2	LH1LH2	HH1LL2	HH1HL2
LH1LH2	LH1HH2	HH1LH2	HH1HH2

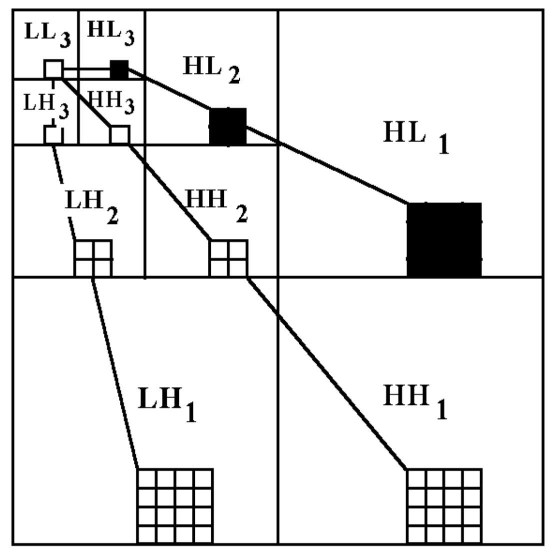

Figure 2. The structure of two level decomposition of Wavelet packet

4. Results and Conclusions

The proposed method is applied separately on the luminance component and both chrominance components of satellite colored image which has 24b/p and its size is 256X256 pixel(see figure 1). All involved parameters, implied within this scheme, were utilized as control parameters to investigate the compression performance of the proposed method [13]. These parameters are; Index of weighting type, inclusion factor, and number of layers. The effects of these parameters were investigated by considering several cases within the allowable range of their values, as shown in tables (1 -2) , while figure (4 illustrates the effect of the control parameters on the compression performance (including the quality of produced luminance component and the produces compression ratio). Figures, (3) , presents the reconstructed RGB image for YIQ color model. From the above results some remarks related to the behavior and performance of the proposed compression method could be presented as follows.

Fig. (4) The original colored image

Table 1

Test color Image	Index of weighting type	If	C.R.	PSNR(dB)
	0	1	4.137	23.658
	1	1	10.684	19.670
	2	1	10.684	19.670
	0	1.6	14.595	17.272
Satellite	1	1.6	11.757	19.157
	2	1.6	11.757	19.157
	0	2	15.194	17.182
	1	2	12.206	19.078
	2	2	12.206	19.078

Number of layers =3,Index of weighting type =1
Inclusion factor =1, C.R.=11.515 ,PSNR = 19.627

Number of layers =2,Index of weighting type =1
Inclusion Factor =1, C.R.=10.684,PSNR = 19.670

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