ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Hyper Spectral Image Compression Using Fast Discrete Curve Let Transform with Entropy Coding

S.Chaithanya
PG Scholar,
Dept of ECE,
NEC, JNTUA, Nellore, AP, India.

K.Penchalaiah
Assistant Professor,
Dept of ECE,
NEC, JNTUA, Nellore, AP, India

ABSTRACT:

The project presents the efficient hyperspectral images compression using discrete curvelet transform and AAC (Adaptive arithmetic) coding. The multi temporal satellite image will be compressed under luma and chroma components to achieve better compression ratio. Here curvelet based adaptive arithmetic entropy coding algorithm will be used for effective compression. Fast discrete curvelet transform is used to decompose the retargeted image into set of coefficients called approximation and detailed one in different orientations. The detailed coefficients contains both noise and edge information. The high frequency subbands represents edges and redundant information extracted from all curved regions. In encoding stage, Adaptive arithmetic coding is involved to shrink the coefficients to represent the image in minimal number of bits. Then bit stream will be transmitted or stored and compression ratio will be measured. At the decoder side, the bit streams are decoded and then perform inverse fast discrete curvelet transformation for reconstructing an image. This system evaluates the performance of AAC coding with various bit rates interms of processing time, mean square error and correlation. The simulated results will be shown that used algorithm has lower complexity with high performance interms of CR and image reconstruction.

KEY WORDS:

Hyper spectral image, fast discrete curvelrt transform, adaptive arithmetic coding, compression ratio, spatial redundancy.

INTRODUCTION:

Digital Image compression address the difficulty of decreasing the amount of data requires to represents a digital image. The primary basis of the reduction process is removal of redundant data.

From the statistical viewpoint, this amounts to transform a 2D pixel array into a statically uncorrelated data set. The data redundancy is not an abstract concept but a mathematically proven entity. If n1 and n2 denote the number of information-carrying units in two data sets that represent the same information, the relative data redundancy [2] of the first data set (the one characterized by n1) can be defined as,

$$R_D = 1 - \frac{1}{C_R} \qquad \text{---------- (1.1)}$$

Where C_R called as compression ratio [2].It is defined as

$$C_R = \frac{n1}{n2} \qquad \text{--------(1.2)}$$

In image compression, three basic data redundancies can be identified as: Coding redundancy,interpixel redundancy, and phychovisal redundancy. Image compression is achieved when one or more of these redundancies are reduced or eliminated. The image compression is mainly used for image transmission and storage. Image transmission applications are in broadcast television; remote sensing via satellite, air-craft, radar, or sonar; teleconferencing; computer communications; and facsimile transmission. Image storage is required most commonly for educational and business documents, medical images that arise in magnetic resonance imaging (MRI), computer tomography (CT) and digital radiology, geological surveys,weather maps, satellite images, and so on.

SIGNIFICANCE OF THIS WORK:

In this project, Image compression based on adaptive wavelet decomposition is presented. Adaptive wavelet decomposition is very useful in various applications, such as image analysis, compression, feature extraction and denoising.

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

For such task, it is important that multiresolution representations take into account the characteristics of the underlying signal and do leave intact important signal characteristics, such as sharp transitions, edges, singularities, and other region of interests. The adaptive lifting technique includes an adaptive update lifting and fixed prediction lifting step. The adaptivity hereof consists that, the system can choose different update filters in two ways; i) the choice is triggered by combining the different norms, ii) Based on the arbitrary Threshold.This image compression based on adaptive wavelet decomposition is implemented using MATLAB programs, and the results compared with Non-adaptive ('Haar') decomposition.

ALGORITHM :

The EZW output stream will have to start with some information to synchronize the decoder. The minimum information required by the decoder is the number of wavelet transform levels used and the initial threshold, if we assume that always the same wavelet transform will be used. Additionally we can send the image dimensions and the image mean. Sending the image mean is useful if we remove it from the image before coding. After imperfect reconstruction the decoder can then replace the imperfect mean by the original mean. This can increase the PSNR significantly. The first step in the EZW coding algorithm is to determine the initial threshold. If we adopt bitplane coding then our initial threshold t0 will be $t0 = 2[\log 2 (\mathrm{Max}(|\gamma(x,y)|))]$------(2.1)Here MAX(.) means the maximum coefficient value in the image and (x,y) denotes the coefficient.

HUFFMAN CODING INTRODUCTION:

Huffman coding is an entropy encoding algorithm used for lossless data compression. The term refers to the use of a variable-length code table for encoding a source symbol (such as a character in a file) where the variable-length code table has been derived in a particular way based on the estimated probability of occurrence for each possible value of the source symbol. It was developed by David A. Huffman while he was a Ph.D. student at MIT, and published in the 1952 paper "A Method for the Construction of Minimum-Redundancy Codes".Huffman coding uses a specific method for choosing the representation for each symbol, resulting in a prefix code (sometimes called "prefix-free codes", that is, the bit string representing some particular symbol is never a prefix of the bit string representing any other symbol) that expresses the most common source symbols using shorter strings of bits than are used for less common source symbols. Huffman was able to design the most efficient compression method of this type: no other mapping of individual source symbols to unique strings of bits will produce a smaller average output size when the actual symbol frequencies agree with those used to create the code. A method was later found to design a Huffman code in linear time if input probabilities (also known as weights) are sorted.For a set of symbols with a uniform probability distribution and a number of members which is a power of two, Huffman coding is equivalent to simple binary block encoding, e.g., ASCII coding. Huffman coding is such a widespread method for creating prefix codes that the term "Huffman code" is widely used as a synonym for "prefix code" even when such a code is not produced by Huffman's algorithm.

Although Huffman's original algorithm is optimal for a symbol-by-symbol coding (i.e. a stream of unrelated symbols) with a known input probability distribution, it is not optimal when the symbol-by-symbol restriction is dropped, or when the probability mass functions are unknown, not identically distributed, or not independent (e.g., "cat" is more common than "cta"). Other methods such as arithmetic coding and LZW coding often have better compression capability: both of these methods can combine an arbitrary number of symbols for more efficient coding, and generally adapt to the actual input statistics, the latter of which is useful when input probabilities are not precisely known or vary significantly within the stream. However, the limitations of Huffman coding should not be overstated; it can be used adaptively, accommodating unknown, changing, or context-dependent probabilities. In the case of known independent and identically-distributed random variables, combining symbols together reduces inefficiency in a way that approaches optimality as the number of symbols combined increases.

3.2 WAVELET TRANSFORM
3.2.1 INTRODUCTION TO WAVELET:

Over the past several years, the wavelet transform has gained widespread acceptance in signal processing in general and in image compression research in particular. In applications such as still image compression, discrete wavelets transform (DWT) based schemes have

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

outperformed other coding schemes like the ones based on DCT. Since there is no need to divide the input image into non-overlapping 2-D blocks and its basis functions have variable length, wavelet-coding schemes at higher compression ratios avoid blocking artifacts. Because of their inherent multi -resolution nature, wavelet-coding schemes are especially suitable for applications where scalability and tolerable degradation are important. Recently the JPEG committee has released its new image coding standard, JPEG-2000, which has been based upon DWT. Basically we use Wavelet Transform (WT) to analyze non-stationary signals, i.e., signals whose frequency response varies in time, as Fourier Transform (FT) is not suitable for such signals.To overcome the limitation of FT, Short Time Fourier Transform (STFT) was proposed. There is only a minor difference between STFT and FT. In STFT, the signal is divided into small segments, where these segments (portions) of the signal can be assumed to be stationary. For this purpose, a window function "w" is chosen. The width of this window in time must be equal to the segment of the signal where it is still be considered stationary. By STFT, one can get time-frequency response of a signal simultaneously, which can't be obtained by FT. The short time Fourier transform for a real continuous signal is defined as:

$$X(f, t) = \int_{-\infty}^{\infty} [x(t)w(t-\tau)^{*}]e^{-} \quad \text{--------(3.1)}$$

Where the length of the window is (t) in time such that we can shift the window by changing value of t,and by varying the value we get different frequency response of the signal segments. The Heisenberg uncertainty principle explains the problem with STFT. This principle states that one cannot know the exact time-frequency representation of a signal, i.e., one cannot know what spectral components exist at what instances of times. What one canknow are the timeintervalsin which certain band of frequencies exists and is called resolution problem. This problem has to do with the widthof the window function that is used, known as the supportof the window. If the window function is narrow, then it is known as compactly supported. The narrower we make the window, the better the time resolution, and better the assumption of the signal to be stationary, but poorer the frequency resolution:

3.2.2 WAVELET TRANSFORM

1-D Continuous wavelet transform

The 1-D continuous wavelet transform is given by:

$$W_f(a, b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)\,dt \quad \text{------------ (3.3)}$$

The inverse 1-D wavelet transform is given by:

$$x(t) = \frac{1}{C}\int_{0}^{\infty}\int_{-\infty}^{\infty} W_f(a,b)\psi_{a,b}(t)\,db\,\frac{da}{a^2} \quad \text{------------ (3.4)}$$

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

$\Psi(\omega)$ is the Fourier transform of the mother wavelet Ψ(t). C is required to be finite, which leads to one of the required properties of a mother wavelet. Since C must be finite, then $\Psi(0) = 0$ to avoid a singularity in the integral, and thus the $\Psi(t)$ must have zero mean. This condition can be stated as $\int_{-\infty}^{\infty} \psi(t)\,dt = 0$ and known as the admissibility condition.

1-D Discrete wavelet transforms:

The discrete wavelets transform (DWT), which transforms a discrete time signal to a discrete wavelet representation. The first step is to discretize the wavelet parameters, which reduce the previously continuous basis set of wavelets to a discrete and orthogonal / orthonormal set of basis wavelets.

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

$\psi_{m,n}(t) = 2^{m/2}\,\psi(2^m t - n)$; m, n ∈Zsuch that $-\infty <$ m, n $< \infty$ -------- (3.5)

The 1-D DWT is given as the inner product of the signal x(t) being transformed with each of the discrete basis functions.

$W_{m,n} = \langle x(t), \psi_{m,n}(t) \rangle$; m, n ∈ □Z ----------- (3.6)

The 1-D inverse DWT is given as:

$$x(t) = \sum_m \sum_n W_{m,n}\,\psi_{m,n}(t)$$; m, n ∈ □Z------------- (3.7)

2-D wavelet transform:

The 1-D DWT can be extended to 2-D transform using separable wavelet filters. With separable filters, applying a 1-D transform to all the rows of the input and then repeating on all of the columns can compute the 2-D transform. When one-level 2-D DWT is applied to an image, four transform coefficient sets are created. As depicted in Figure 3.2(c), the four sets are LL, HL, LH, and HH, where the first letter corresponds to applying either a low pass or high pass filter to the rows, and the second letter refers to the filter applied to the columns.

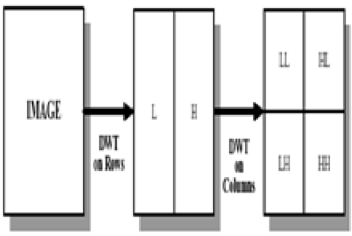


Figure 3.2Block Diagram of DWT (a) Original Image (b) Output image after the 1-D applied on Row input (c) Output image after the second 1-D applied on row input

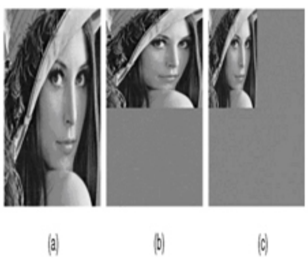


Figure 3.3 DWT for Lena image (a) Original Image (b) Output image after the 1-D applied on column input (c) Output image after the second 1-D applied on row inputThe Two-Dimensional DWT (2D-DWT) converts images from spatial domain to frequency domain. At each level of the wavelet decomposition, each column of an image is first transformed using a 1D vertical analysis filter-bank. The same filter-bank is then applied horizontally to each row of the filtered and sub sampled data. One-level of wavelet decomposition produces four filtered and sub sampled images, referred to as sub bands. The upper and lower areas of Fig. 3.3(b), respectively, represent the low pass and high pass coefficients after vertical 1D-DWT and sub sampling. The result of the horizontal 1D-DWT and sub sampling to form a 2D-DWT output image is shown in Fig.3.3(c).We can use multiple levels of wavelet transforms to concentrate data energy in the lowest sampled bands. Specifically, the LL sub band in fig 2.1(c) can be transformed again to form LL2, HL2, LH2, and HH2 sub bands, producing a two-level wavelet transform. An (R-1) level wavelet decomposition is associated with R resolution levels numbered from 0 to (R-1), with 0 and (R-1) corresponding to the coarsest and finest resolutions.

EXISTING METHOD:

•Huffman Coding
•SPIHT based compression
•Discrete cosine and wavelet transformation

DRAWBACKS:

•Less compression ratio and dictionary is required at decoding
•Complexity coder with high bit error rate
•Blocking and ringing artifacts during reconstruction

REQUIREMENT SPECIFICATION SOFTWARE REQUIREMENT

•MATLAB 7.5 and above versions
•Image Processing Toolbox

Hardware Requirements

•Pentium(R) D CPU 3GHZ
•1 GB of RAM
•500 GB of Hard disk

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

PROPOSED SYSTEM DESIGN:

pre-processing step involving a special partitioning of phase-space followed by the ridgelet transform which is applied to blocks of data that are well localized in space and frequency.In the last two or three years, however, curvelets have actually been redesigned in a effort to make them easier to use and understand. As a result, the new construction is considerably simpler and totally transparent. What is interesting here is that the new mathematical architecture suggests innovative algorithmic strategies, and provides the opportunity to improve upon earlier implementations. The two new fast discrete curvelet transforms (FDCTs) which are simpler, faster, and less redundant than existing proposals:

• Curvelets via USFFT, and
• Curvelets via Wrapping.

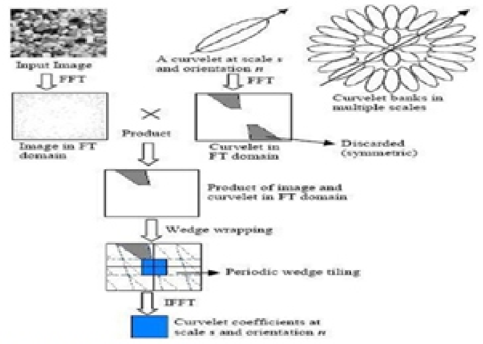


Fig. 1. FDCT via wrapping.

The block size can be changed at each scale level. The wrapping construction is shown in Fig. 1. If $f[t_1, t_2], 0 \leq t_1, t_2 < n$ is taken to be a Cartesian array and $\hat{f}[n1, n2]$ denotes its 2-D discrete Fourier transform, then the architecture of the FDCT via wrapping is as follows.

1) Apply the 2-D FFT and obtain Fourier samples,

$$\hat{f}[n_1, n_2], \qquad -\frac{n}{2} \leq n_1, \qquad n_2 < \frac{n}{2}.$$

2) For each scale j and angle l, form the product

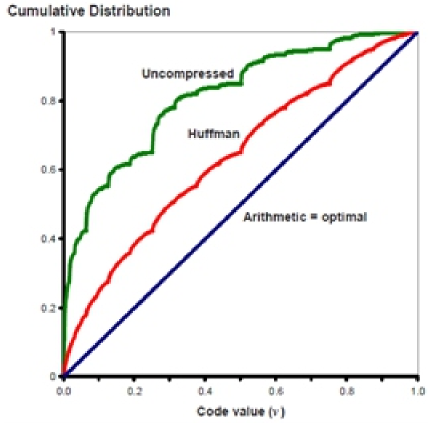
$$\tilde{U}_{j,l}[n_1, n_2]\hat{f}[n_1, n_2]$$

where Uj,l [n1, n2] is the discrete localizing window

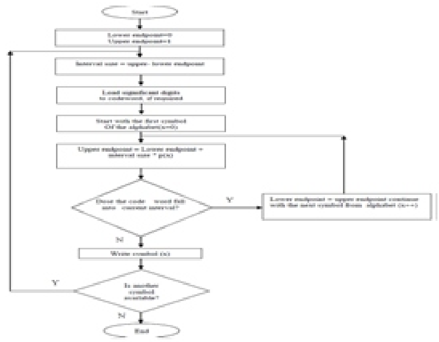
3) Wrap this product around the origin and obtain

$$\tilde{f}_{j,l}[n_1, n_2] = W(\tilde{U}_{j,l}\hat{f})[n_1, n_2]$$

4) Apply the inverse 2-D FFT to each ˜ fj,l , hence collecting the discrete coefficients CD (j, l, k).It introduces the notation and equations that describe arithmetic encoding, followed by a detailed example. Fundamentally, the arithmetic encoding process consists of creating a sequence of nested intervals.

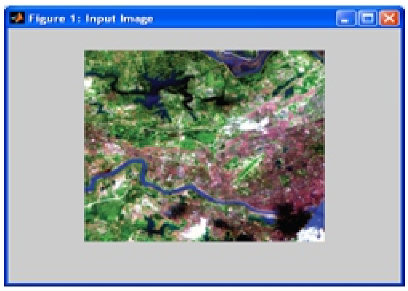


Flow chart of Arithmetic coding:



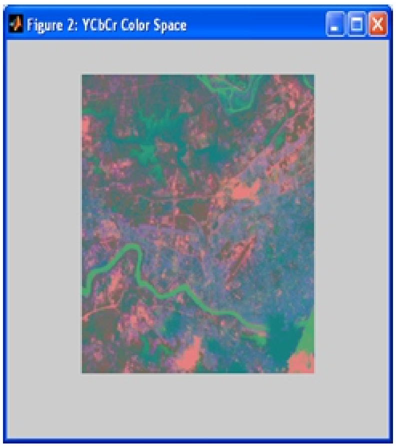
SIMULATED RESULTS:

a)Input image:

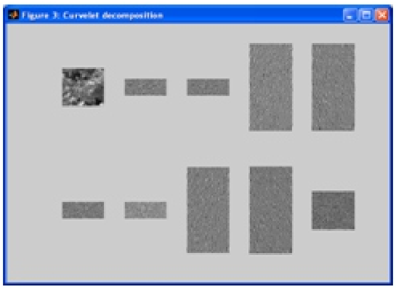


ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

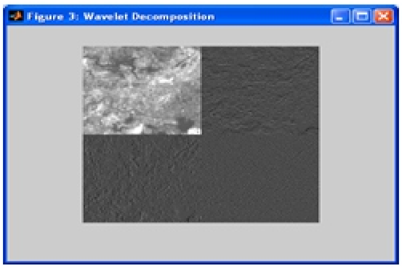
b)Color Space Conversion:



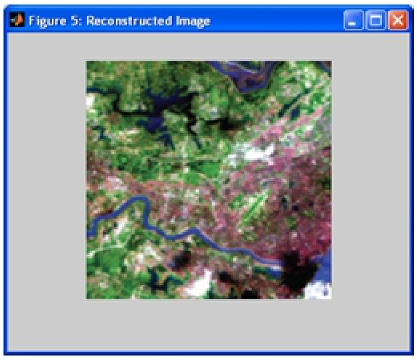
c)FDCT Decomposition:



d)LWT Decomposition:



e)Reconstructed Image:



i)using SPIHT
ii) using AAC

CONCLUSION:

This project presented that HS image compression using lossy and lossless coding for analysis of compression effect based on wavelet based set partitioning in hierarchical trees coding and curvelet based arithmetic coding. Wavelet based speck coding was used to compress image by considering significant coefficients based on priority. Adaptive arithmetic coding provided better encoding performance with discrete curvelet transform. It represented an image interms of detailed coefficients in all directions. The simulated results shows that, entropy coding provides better compression ratio rather than SPIHT coding and Image quality also can preserve it with entropy lossless Coding. Further this system will be enhanced by modifying used encoding algorithm with context adaptive coding to preserve the image details and with low complexity.

REFERENCES:

[1] H. F. Grahn and P. Geladi, Techniques and Applications of Hyperspectral Image Analysis. Chichester, U.K.: Wiley, 2007.
[2] C.Huo, R. Zhang, and T. Peng, “Lossless compression of hyperspectral images based on searching optimal multibands for prediction,” IEEE Geosci. Remote Sens. Lett., vol. 6, no. 2, pp. 339–343, Apr. 2009.
[3] J. Serra-Sagristà and F. Aulí-Llinàs, “Remote sensing data compression,” in Computational Intelligence for Remote Sensing. Berlin, Germany: Springer-Verlag, Jun. 2008, pp. 27–61.
[4] J.Wang and C. Chang, “Independent component analysis-based dimensionality reduction with applications in hyperspectral image analysis,” IEEE Trans. Geosci. Remote Sens., vol. 44, no. 6, pp. 1586–1600, Jun.2006.
[5] X. Tang and W. A. Pearlman, “Three-dimensional wavelet-based compression.Of hyperspectral images,” in Hyperspectral Data Compression, G. Motta, F. Rizzo, and A. Storer, Eds. : Springer, 2006, ch. 10, pp. 273–278.