RESEARCH ARTICLE OPEN ACCESS

Comparative Performance Analysis of High Dimensional Data Reduction Using DWT and PCA

Ms. Sneha R. Burnase *, Ms. Shanti Swamy **
*(Department of Electronics Engg, RTMNU, KITS Ramtek, MS, INDIA Email: sneharburnase@gmail.com)
** (Department of Electronics Engg, RTMNU, KITS Ramtek, MS, INDIA Email: shantiswamy@gmail.com)

ABSTRACT
The hyperspectral image acquisition systems are rapidly developing and providing data with more and more dimensionality. However, unless we develop suitable algorithms for processing this data, no useful information can be extracted. This high dimensional data requires special considerations beyond the conventional processing techniques. Precisely, if we develop a pre-processing stage which works on the key problem of 'very large Thus, reduction of hyperspectral images is chosen as the fundamental research area. Within the variety of already available techniques for hyperspectral image reduction, the method of Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) chosen for analysis. This paper includes reduction of hyperspectral image using these two methods and computational time, reduction ratio, MSE, PSNR are the parameters to be analysed.

Keywords - DWT, Hyperspectral, PCA, PSNR, Reduction ratio.

I. INTRODUCTION

The introduction of the paper should explain the nature of the problem, previous work, purpose, and the contribution of the paper. The contents of each section may be provided to understand easily about the paper. Hyperspectral remote sensing provides high-resolution spectral data and the potential for remote discrimination between subtle differences in ground covers. However, the high-dimensional data space generated by the hyperspectral sensors creates a new challenge for conventional spectral data analysis techniques.

It has been proven that high-dimensional data spaces have the following properties:

- The volume of a hypercube concentrates in the corners, and
- The volume of a hypersphere or hyperellipsoid concentrates in an outer shell.

This property of the high-dimensional space implies that with limited training data, much of the hyperspectral data space is empty. Principally, two solutions exist:
1) Provide larger sets of training data or
2) Reduce the dimensionality by extracting pertinent features from the hyperspectral signals.

Spectral images are collected by remote sensing instruments, which are typically carried by airplanes or satellites. As these platforms move along their flight paths, the instruments scan across a swath perpendicular to the direction of motion. The data from a series of such swaths form a two-dimensional image.

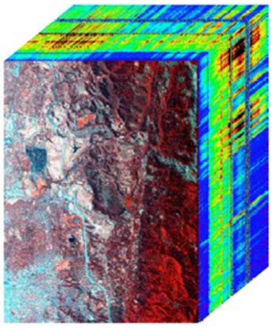

Fig.1 A typical hyperspectral Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) datacube of 224 bands

A fundamental reason why the Discrete wavelet Transform is an excellent tool for feature extraction is its inherent multi resolution approach to signal analysis. Projecting the signal onto a basis of wavelet functions can separate the fine-scale and largescale information of a hyperspectral signal.

On the other hand Principal Component Analysis (PCA) is the general name for a technique which uses sophisticated underlying mathematical principles to transforms a number of possibly correlated variables into a smaller number of variables called principal components.

The analysis of spectral imagery typically requires atmospheric compensation, dimensionality reduction, and image enhancement. The purpose of implementing these procedures is to facilitate usage of spectral libraries, to reduce the computational complexity and to eliminate noise. A fundamental principle when implementing these procedures is that all the useful information must be preserved. Both methods are applied on the same hyperspectral image and parameters are observed.

II. DISCRETE WAVELET TRANSFORM (DWT)

The DWT can be described mathematically as a set of inner products between a finite-length sequence and a discretized wavelet basis. Each inner product results in a wavelet transform coefficient.

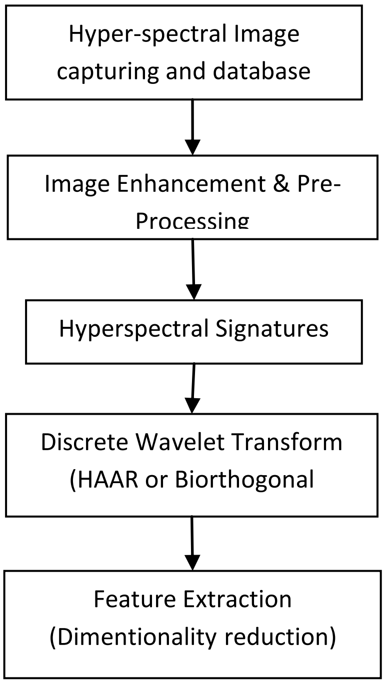

Fig.2 Algorithm for hyperspectral image reduction

A. DYADIC TREE ALGORITHM

In this application of the DWT, corresponds to a hyperspectral signal, where is the spectral band or channel number. The sampling was conducted in a manner where the spectral bands are numerous, have equal bandwidth, and are equally spaced and since the wavelet basis is made of scaled, or dilated, and translated versions of a mother wavelet, the DWT can provide a de-tailed, as well as a global, view of the input hyperspectral signal. In practice, the dyadic DWT can be implemented in a computationally efficient manner via the dyadic filter tree algorithm. The basic idea behind the fast algorithm is to represent the wavelet basis as a set of high-pass and low-pass filters in a filter bank.four level decomposition dyadic tree is shown in fig. 1.The outputs of the low-pass branch are called wavelet approximation coefficients in equation 1, and the outputs of the high-pass branch are called wavelet detail coefficients. Mathematiacally can be given as

$$A_{j+1(i)} = \sum_{l=0}^{L-1} H(l).A_j(2.i+l) \qquad \text{---------(1)}$$

$$D_{j+1(i)} = \sum_{l=0}^{L-1} G(l).A_j(2.i+l) \qquad \text{------------(2)}$$

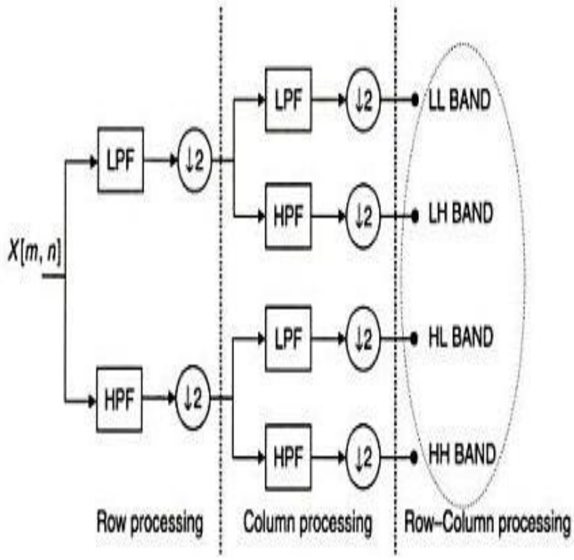

Fig.3 Dyadic tree structure for decomposition and separating approximation and detail.

B. FEATURE EXTRACTION

The wavelet decomposition coefficients include all information in the original signal. Thus, multiscale features of the original hyperspectral signal can be extracted directly from the wavelet decomposition coefficients. Receiver operating characteristics (ROC) curves are used to evaluate the class-discriminating capability of each wavelet co-efficient and determine the optimum subset of wavelet coefficients.

III. PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal Components Analysis (PCA) is the most widely used linear-dimension method based on second order statistics. PCA is also known as the Karhunen-Loeve transform, singular value decomposition (SVD), empirical orthogonal function (EOF), and Hotteling transform. PCA is a mathematical procedure that facilitates the simplification of large data sets by transforming a number of correlated variables into a smaller number of uncorrelated variables called principal components.fif. shows basic steps in PCA method.

Fig. 4 PCA basic method algorithm used in Hyperspectral Reduction.

C. Types of Wavelet used

1) HAAR Wavelet

Haar wavelet is the first and simplest. The Haar wavelet transform has the advantages of being conceptually simple, fast and memory efficient, since it can be calculated in place without a temporary array. Furthermore, it is exactly reversible without the edge effects that are a problem of other wavelet transforms.

$$\psi(n) = \begin{cases} 1 & 0 \le n \le \frac{1}{2} \\ -1 & \frac{1}{2} \le n \le 1 \\ 0 & \text{otherwise} \end{cases}$$

The high-pass and low-pass FIRs representing the Haar mother wavelet have only two samples $G = \left[\frac{1}{\sqrt{2}}\ \frac{1}{\sqrt{2}}\right]$ and $H = \left[\frac{1}{\sqrt{2}}\ \frac{1}{\sqrt{2}}\right]$ which are the shortest possible wavelet filters.

2) **Bio-orthogonal Wavelet**

This family of wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction. By using two wavelets, one for decomposition (on the left side) and the other for reconstruction (on the right side) instead of the same single one, interesting properties are derived. Biorthogonal Wavelets are families of compactly supported symmetric wavelets. The symmetry of the filter coefficients is often desirable since it results in linear phase of the transfer function. In the biorthogonal case, rather than having one scaling and wavelet function, there are two scaling functions that may generate different multiresolution analysis, and accordingly two different wavelet functions.

The dual scaling and wavelet functions have the following properties:

1. They are zero outside of a segment.
2. The calculation algorithms are maintained, and thus very simple.
3. The associated filters are symmetrical.
4. The functions used in the calculations are easier to build numerically than those used in the Daubechies wavelets.

***D.* QUADTREE DECOMPOSITION ALGORITHM**

Quadtree decomposition algorithm is used to subdividethe hyper-spectral image into smaller image quadrants. The recursive decomposition can be represented in a tree. At the top level of the tree (root), the decomposition starts. The root corresponds to the entire binary image. It is connected to four child nodes, which represent each quadrant from left to right and the NW, NE,mSW, and SE quadrants respectively. If the child is gray, it is again connected to four other children. The tree will continue until the quadrants do not need any further subdivision. In the example, the NE, SE, and SW 2x2 pixel quadrants are regions of interest because the child nodes at the second tree level are either gray or black. The NW region is entirely white, which represents a region without the presence of the desired spectral signatures.The essential component of this region autofocus application is the quadtree implementation.

Parameters observed after applying these methods on Hyperspectral image of 33 bands and considering 10 bands amongst that.

TABLE I

parameters observed after reduction of high dimensional data

Parameter	**No. Of bands selected=10**		
	DWT (HAAR)	**DWT (Biorthogonal)**	**PCA**
Reduction Ratio	50.01	50.35	42.63
Computational Time	17 sec	20.01 sec	34.43 sec
MSE	0.0090	0.0069	0.0083
PSNR	68.21	69.96	68.91

IV. CONCLUSIONS

From the parameters observed, we can conclude that for same type of hyperspectral image and number of bands different values of parameters like reduction ratio, computational time, Mean Square error rate (MSE) and Peak Signal To Noise (PSNR).BY using Haar Wavelet taking less computational time and also reduction ratio is higher but in case of biorthogonal psnr value we are getting higher. In case of PCA Time required is more but reduction factor is improved.

REFERENCES

JOURNAL PAPERS:

[1] The Effect of the Spectral Band Selection Method on Hyperspectral Images Segmentation Accuracy Ali Bakhshi, Mohammad Hassan Ghassemian, and Alireza Ahmadifard, International Journal of Computer Theory and Engineering, Vol. 4, No. 3, June 2012

[2] Dimensionality Reduction and Classification of Hyperspectral Image Data Using Sequences of Extended Morphological Transformations Antonio Plaza, Member, IEEE, Pablo Martínez, Javier Plaza, and Rosa Pérez, , IEEE transaction 2008.

[3] Multivariate denoising using wavelets and principal component analysis Computational Statistics & Data Analysis by Aminghafari, M., Cheze, N. & Poggi, J.-M. (2006). 50, 2381–2398.

[4] Ancona, M., Cazzola, W., Raffo, P. & Corvi, M. (2002). Image Database Retrieval Using Wavelet Packets Compressed Data. In Proceedings of the Sixth SIMAI National Conference. Chia Laguna, Italy.

[5] Dimensionality Reduction of Hyperspectral Data Using Discrete Wavelet Transform Feature Extraction Lori Mann Bruce, Senior Member, IEEE, Cliff H. Koger, and Jiang Li, Student, Member, IEEE Transactions on Geoscience And Remote Sensing, Vol. 40, NO. 10, October 2002.

[6] Image Denoising for Gaussian Noise Reduction in Bionics Using DWT Technique Iram Sami, 2Abhishek Thakur, 3Rajesh Kumar IJECT Vol. 4, Issue Spl - 3, April - June 2013

[7] Projection Pursuit-Based Dimensionality Reduction for Hyperspectral Analysis, Haleh Safavi, Chein-I Chang, and Antonio J. Plaza