IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676, p-ISSN: 2320-3331
PP 13-16
www.iosrjournals.org

Hyperspectral Image Reduction using Discrete Wavelet Transform

Miss Sneha R. Burnase[1], Miss Shanti Swamy[2]
[1,2] Electronics Engg., K.I.T.S, Ramtek, India

ABSTRACT : *For any area of engineering, the development in 'data acquisition hardware' and the 'development in data processing software' go hand in hand. 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 number of labeled samples', then the conventional approaches can be retained for rest of the algorithm. 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) is chosen for analysis because of the wavelet's inherent multi-resolution properties. This paper includes reduction of hyperspectral image using various wavelet.*

Keywords: *hyperspectral, biorthogonal, wavelet, HAAR*

I. INTRODUCTION

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 epty. Principally, two solutions exist:
1) Provide larger sets of training data or
2) Reduce the dimensionality by extracting pertinent features from the hyperspectral signals.
When considering solution 1) it must be taken into account that as the number of dimensions increase, the sample size of the training data needs to increase exponentially in order to have valuable estimates of multivariate statistics . Considering the impracticality of this scenario when using a hyperspectral sensor with hundreds or thousands of spectral bands. Thus, solution 2) must be considered, creating a need for feature extraction methods that can reduce the data space dimensions without losing the original information that allows for the separation of classes.

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.

Sensors that collect remote sensing data are typically optoelectronic systems that measure reflected solar irradiance. Spectral imagers record this reflected energy at a variety of wavelengths. Early earth imaging systems, such as Landsat, did this in a few relatively broad bands that were not-contiguous, that is, there were gaps in the spectral coverage. Hyperspectral sensors typically measure brightness in hundreds of narrow, contiguous wavelength bands so that for each pixel in an image, a detailed spectral signature can be derived. The term hyperspectral is used to reflect the large number of bands, but the contiguous (complete) spectral coverage is also an important component to the definition. The bands need to be narrow enough to resolve the spectral features for targets of interest, a requirement that can lead to bands from a few nanometers in width to tens of nanometers. As shown in fig. a representative hyperspectral image, or hypercube, with spatial dimensions 1024 by 614, and spectral data of 224 contiguous bands, from 0.4 µm to 2.5 µm. This image is a red, green, blue composite formed using bands 43 (769.68 nm), 17 (539.40 nm), and 10 (470.76 nm).

In the paper titled "Dimensionality Reduction of Hyperspectral Data Using Discrete Wavelet Transform Feature Extraction" by Lori Mann Bruce, Senior Member, IEEE published in IEEE Transactions on Geoscience And Remote Sensing, Vol. 40, NO. 10, October 2002, it is proposed that the wavelet transform is an excellent tool for feature extraction is its inherent multiresolution approach to signal analysis Projecting the signal onto a basis of wavelet functions can separate the fine-scale and large-scale information of a hyperspectral signal and finally they conclude that DWT is linear, it could be an appropriate choice as a data dimensionality reduction tool for the application of linear spectral unmixing.

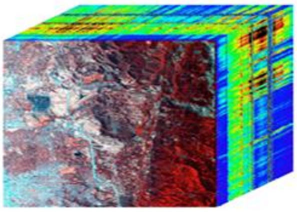

Fig.1 A typical hyperspectral Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) datacube of 224 bands

1.1) Discrete Wavelet Transform (DWT)

A fundamental reason why the 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. Multi resolution approaches have previously been applied to spectral analysis. For example, a common method of data analysis is derivative spectroscopy. Typically, a smoothing operator is followed by a derivative operator to detect pertinent "hills" and "valleys" in the spectral curves. The resolution, or width, of the operators is varied de-pending on the scale of the features to be detected. Similarly, the wavelet transform uses a varying width operator; however, the operator is not restricted to being a derivative. The fundamental operator is referred to as the mother wavelet, and any function $\psi(\lambda)$ can serve as the mother wavelet, as long as it satisfies the following admissibility condition

$$\int_{-\infty}^{+\infty} \frac{|\Im(\Psi(\lambda))|^2}{\omega} \, d\omega < \infty : \quad (1)$$

where $\Im(.)$ denotes the Fourier transform,
'ω' is the Fourier domain variable.

This condition can be described simply in the following way:
1) the mother wavelet function must oscillate and have an average value of zero, and
2) the mother wavelet must have exponential decay and exhibit "compact support." Once a mother wavelet is selected, the wavelet transform can be used to decompose a signal according to scale, allowing to separate the fine-scale (detail) behavior from the large-scale (approximation) behavior of the signal. This is typically done in an iterative fashion using the dyadic discrete wavelet trans-form (DWT), where scales $124\ldots2M$ are utilized.

Thus, the wavelet transform not only provides a concise mathematical means for generalizing the analysis operator; it also provides a mathematical construct for systematically varying the operator's width or scale. For these reasons, it is proposed that the wavelet transform can be a productive tool for hyperspectral feature extraction. The wavelet-based features are utilized in a fully automated ground cover classification system, and the results are compared to those of a similar system where conventional feature extraction methods are utilized.

The above background information about the DWT can be summarized as two points:
1) the fine-scale and large-scale in-formation in the original signal is separated into the wavelet detail and approximation coefficients, respectively, and
2) 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. Infinitely many choices of features could be extracted, including the coefficients themselves or any combination of the coefficients. Process flow is as given in next fig.

1.2) Types of Wavelet used

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. Haar wavelet is discontinuous, and resembles a step function hown in fig. 3

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

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.

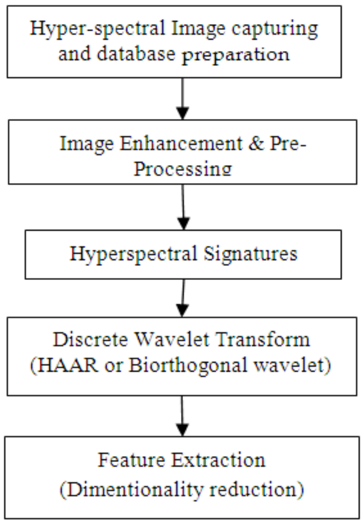

Fig. 2 Algorithm for hyperspectral image reduction

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.

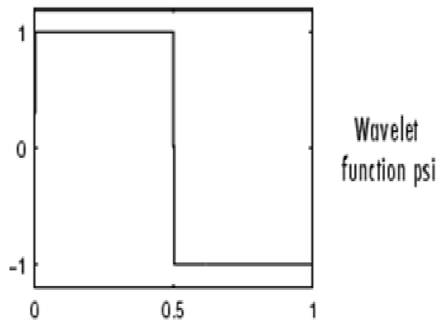

Fig. 3) HAAR Wavelet

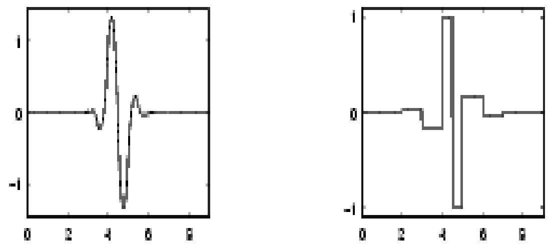

Fig.4) Biorthogonal Wavelets

II. CONCLUSION

Hyperspectral image reduction can be done using various method but discrete wavelet transform has certain advantages. Discrete wavelet transform can be obtained by various wavelets like HAAR and Biorthogonal Wavelets. Review says that Computational Time required for Biorthogonal is Less than HAAR Hence in future We can also compare performance of these two techniques and find PSNR ratio. We can also Compare the performance of other nonlinear method with these methods.

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

Books:

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