An Application of Wavelet Based Dimension Reduction to AIRS Data

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Abstract- Hyperspectral sensors provide much richer information than comparable multispectral sensors. However currently we do not have sufficient recourses to compute results based on all the gathered information. One way to approach this problem is to perform dimension reduction [1] as pre-processing, i.e to apply a transformation that brings data from a high order dimension to a low order dimension. Wavelet spectral analysis of hyperspectral images has been proposed as a method for dimension reduction and has shown promising results over the traditional Principal Component Analysis (PCA) technique. The Atmospheric Infrared Sounder (AIRS) [2] instrument data, designed to measure the Earth's atmospheric water vapor and temperature profiles on a global scale. AIRS has more than 2,000 channels and hence becomes a good candidate dimension reduction. The objective of this work is to extend and apply Wavelet based Dimension Reduction over AIRS data.

Keywords: AIRS Sensing, Dimension Reduction, Wavelet Decomposition

I. INTRODUCTION

Recently developed hyperspectral sensors provide much richer information than comparable multispectral sensors. But traditional methods that have been designed for multispectral data are not always adapted to hyperspectral data. Conventional classification methods, for example, cannot be used without dimension reduction preprocessing; due to the "curse of dimensionality," which refers to the fact that the sample size needed to estimate a function of several variables to a given degree of accuracy grows exponentially with the number of variables. One way to approach this problem is to perform dimension reduction as a pre-processing.

Traditionally, Principal Component Analysis (PCA) has been the technique of choice for dimension reduction. Wavelet spectral analysis of hyperspectral images has been recently proposed as a method for dimension reduction [1] and, when tested for the classification of AVIRIS data, has shown promising results. One of the interesting features of wavelet spectral analysis reduction is that it can ignore data anomalies due to the use of low pass filters.

In this article, we propose to extend the wavelet analysis reduction method to AIRS data. The Atmospheric Infrared Sounder (AIRS) [2] instrument suite is designed to measure the Earth's atmospheric water vapor and temperature profiles on a global scale. With more than 2,000 channels, the AIRS Infrared data represent a good candidate for dimension reduction, and especially wavelet reduction.

II. DATA AND DIMENSION REDUCTION TECHNIQUES

A. Wavelet-Based Dimension Reduction

As a definition, data or dimension reduction is a process designed to reduce data volumes by filtering out specific redundant information. It is also commonly used for performing image fusion. Such a feature vector dimensionality reduction has been pursued in several different ways, but traditionally, Principal Component Analysis (PCA) has been the technique of choice.

Recently, we developed a new wavelet-based data reduction method and implemented it both sequentially and on a Commercial-Off-The-Shelf (COTS)-based architecture, the Beowulf. The principle of this novel wavelet-based method is to apply a discrete one-dimensional wavelet transform in the spectral domain and at each pixel. This transform decomposes the signature of each pixel into a set of composite bands that are linear, weighted combinations of the original spectral bands. Figure 1 shows an example of the actual signature of one class (Corn) for 192 bands of an AVIRIS hyperspectal dataset, and different levels of wavelet decomposition of this

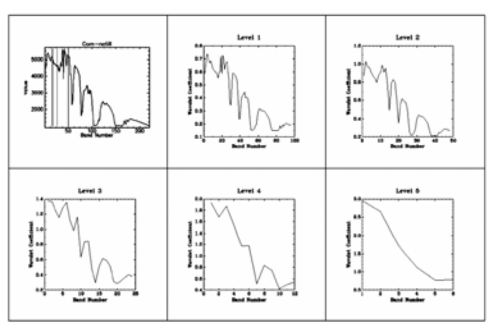

Figure 1 - ***Example of the Corn Spectral Signature And Different Levels of Wavelet Decomposition***

spectral signature. The typical Discrete Wavelet transform [3] is illustrated in Figure 2, over a sample [X] voxel data, i.e. over the 1-D signal representing the spectral signature of that pixel. When the number of bands is reduced, the structure of the spectral signature becomes smoother than the structure of the original signature, but the signal still shows the most important features for several levels. The detailed description of the algorithm is then:

(1) Multi-resolution wavelet decomposition of each pixel 1-D spectral signature.
(2) At each level of decomposition:
    (2.1) Reconstruction using only low-pass information.
    (2.2) Similarity measure (e.g., correlation) between original signature and reconstructed signature for that decomposition level.
    (2.3) Record that level in a histogram if it satisfies a quality of "good" reconstruction, defined by a percentage-threshold.
(3) From the histogram, choose the optimum level of decomposition. and build the corresponding dimension reduced image.

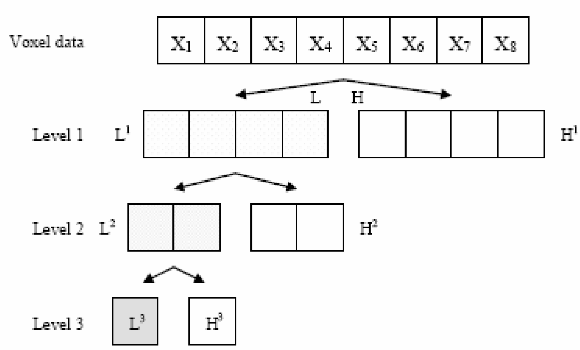

Figure 2 - ***Discrete Wavelet Decomposition Transform***

From a complexity point of a view, the whole algorithm complexity is in the order of $O(MN)$, where M is the number of pixels in the spatial domain and N is the number of bands. The total estimated complexity of PCA is $O(MN^2+N^3)$, which shows that the computational efficiency of the wavelet reduction technique is superior to the efficiency of the PCA method.

We validated the wavelet-based reduction using different supervised classifications of hyperspectral AVIRIS data. The results show that our new wavelet-based dimension reduction method provides a greater computational efficiency as well as a better or comparable overall classification than the widely used PCA method [1]. The wavelet decomposition operation has been shown to be at least as accurate as and more computationally efficient than the PCA dimension reduction mechanism.

B. AIRS data

The Atmospheric Infrared Sounder (AIRS) instrument suite is used to create global Earth three-dimensional maps of temperature, humidity and clouds in the Earth's atmosphere with great accuracy. This will lead to better weather forecasts and will be used to study and characterize and eventually predict the global climate.

The AIRS [4][5] system is made up of three of the six Aqua instruments - AIRS itself, which is an infrared sounder with 2378 spectral channels, complemented with a 4-channel visible/near-infrared imaging module; Advanced Microwave Sounding Unit-A (AMSU-A), which is a 15-channel microwave temperature sounder; and Humidity Sounder for Brazil (HSB), which is a 4-channel microwave humidity sounder. These instruments are aligned with each other scanning the atmosphere in a synchronized way, and providing simultaneous multispectral views of a highly variable target.

Generally, AIRS data is reduced depending on the application by choosing "appropriately" the channels to process, for example utilizing the 281 reduced channels being distributed to weather centers[6][7]. In order to optimize the information content kept in the processing, better and automatic data reduction algorithms are needed that would reduce the amount of data to process while keeping data accurate and meaningful.

Interval #	Spectral Cuton (μm)	Spectral Cutoff (μm)	# bands	Starting Channel	Ending Channel
1	3.7364	3.9169	118	0	117
2	4.11	4.3291	130	118	247
3	3.9149	4.11	116	248	363
4	4.3271	4.6085	150	364	513
5	6.9356	7.4769	192	514	705
6	6.2003	6.4934	104	706	809
7	6.5504	6.85	106	810	915
8	7.4745	7.7921	94	916	1,009
9	7.8605	8.22	106	1,010	1,115
10	8.8073	9.4796	159	1,116	1,274
11	9.565	10.275	167	1,275	1,441
12	10.275	10.985	167	1,442	1,608
13	11.0704	11.7512	161	1,609	1,769
14	11.7431	12.685	167	1,770	1,936
15	12.7989	13.7457	167	1,937	2,103
16	13.7377	14.5533	144	2,104	2,247
17	14.6672	15.4	130	2,248	2,377

Table I – ***Intervals for AIRS InfraRed Spectrometer Level 1B Data***

The dataset used for this study was acquired on January 1, 2003. The AIRS Infrared (IR) level 1B data set contains AIRS infrared calibrated and geolocated radiances in milliWatts/m**2/cm**-1/steradian. This data set is generated from AIRS level 1A digital numbers (DN), which includes 2378 infrared channels in the 3.74 to 15.4 μm region of the spectrum. A day's worth of AIRS data is divided into 240 scenes each of 6 minutes duration. For the AIRS infrared measurements, an individual scene consists of 135 scan lines containing 90 cross-track footprints; thus there is a total of 135 x 90 = 12,150 footprints per AIRS IR scene. The 2378 infrared channels have been broken into three major intervals:

- 3.74 - 4.61 micron, channel 1865 – 2378
- 6.20 - 8.22 micron, channel 1263 – 1864
- 8.80 - 15.4 micron, channel 1 – 1262

Each of these intervals is further divided into subintervals for a total of 17 subintervals [8], not equally spaced as illustrated in Table 1.

III. EXPERIMENTAL WORK

In this paper we will present a comparison of processing of forward model using the reduced data set using the Wavelet based method as compared to the 281 pre-selected channels. The processing using the wavelet based dimension reduction of AIRS data involves the following steps

1. Simulate the AIRS brightness temperature spectrum for a given profile using all the 2378 channels.
2. Generate the AIRS brightness temperature spectrum using the new frequency depending on the wavelet based reduction level.
3. Since the frequencies are not same as the original dataset and the fast radioactive transfer scheme works on the predefined set, we use linear interpolation of the original spectrum to generate the brightness temperature.

Generalization of Wavelet-Based Dimension Reduction to AIRS data

In order to support AIRS data, the wavelet dimension reduction technique needs to handle multiple intervals with different spacing between these intervals. We have conducted some studies using the correlation depending on the number of channels selected manually. The original and the reduced channels spectral signature is showed in figure 3 and 4 respectively.

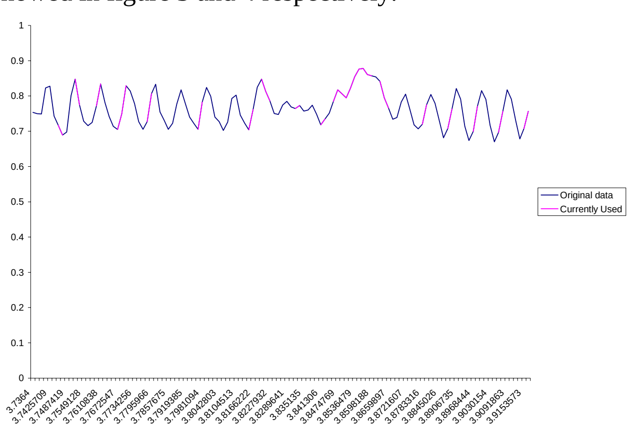

Figure 3 –Radiance for first interval of *AIRS InfraRed Spectrometer Level 1B Data showing the original data and selected channels*

In one interval, the bands are supposed to be contiguous in the spectral domain, but the number of channels selected from each interval differs. Therefore, the regular wavelet reduction algorithm cannot be applied as it is, on each interval.

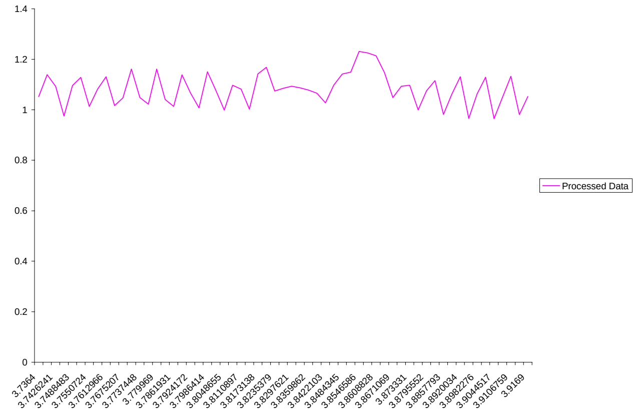

Figure 4 –Radiance for first interval of *AIRS InfraRed Spectrometer Level 1B Data showing the processed channels*

The decomposed AIRS output is composed of the decomposed output of each considered interval depending on the number which is pre-selected depending on the priori information. These channels are appended to each other. This mechanism is illustrated in Figure 5. The AIRS data interval decomposition can be done during the pre-processing stage.

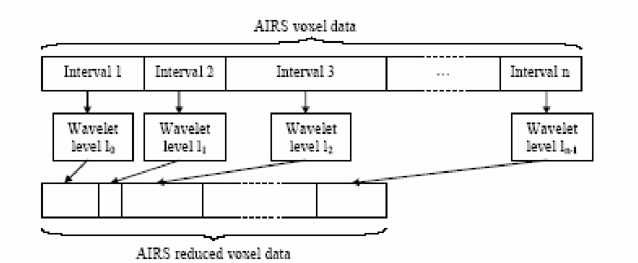

Figure 5 – AIRS Wavelet Dimension Reduction Processing

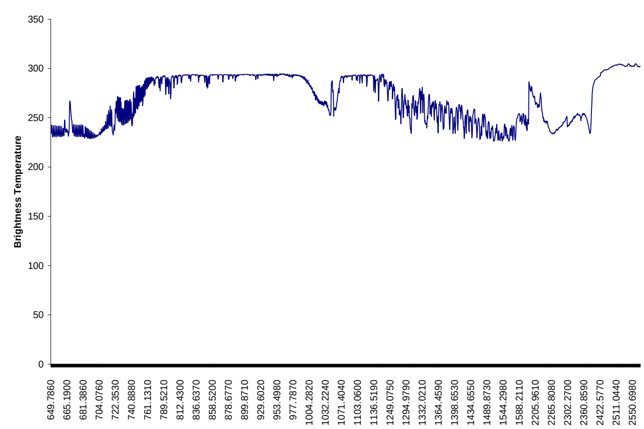

Figure 4 – Brightness temperature profile for *AIRS InfraRed Spectrometer Level 1B Data*

These results show that different sub-intervals have different properties, including anomalies that yield different optimum levels for dimension reduction. Currently, scientists choose channels by looking at low correlation for certain intervals and high correlation for other intervals. This selection of bands depends on prior information about the information contained in the interval.

IV. Conclusion And Future Work

We generalized the wavelet-based dimension reduction algorithm for the 2378 bands-AIRS data. Results showed that additional information content about the data needs to be incorporated. We have shown the output of Brightness temperature profile for the processed data. In future we will study the difference of the Brightness temperature profile to the original data and compute an "error" covariance matrix. Then, using an error covariance matrix for the retrieval first guess, we can calculate a retrieval error covariance.

V. References

[1] S. Kaewpijit, J. Le Moigne, and T. El-Ghazawi, 2003, “Automatic Reduction of Hyperspectral Imagery Using Wavelet Spectral Analysis,” IEEE Transactions on Geoscience and Remote Sensing, Vol.41, No.4, pp.863-871, April 2003.

[2] AIRS Atmospheric Infrared Sounder – Home Page, http://www-airs.jpl.nasa.gov/

[3] I. Daubechies, Ten Lectures on Wavelets, SIAM 1992

[4] AIRS IR Level 1B Calibrated, Geolocated Radiances, http://daac.gsfc.nasa.gov/atmodyn/airs/airsL1B_Rad.html

[5] T. S. Pagano, D. A. Elliota, M. R. Gunsona, H. H. Aumanna, S. L.Gaisera, N. Dehghania, K. Overoyeb, Operational Readiness for the Atmospheric Infrared Sounder (AIRS) on the Earth Observing System Aqua spacecraft, SPIE 4483-04, August 2001.

[6] J. Joiner, L. Rokke, Variational cloud-clearing with TOVS data, Quarterly Journal of the Royal Meteorological Society, 126, pp. 725-748, 2000.

[7] J. Joiner, P. Poli, D. Frank, and H.C. Liu, Detection of Cloud-Affected AIRS Channels Using an Adjacent-Pixel Approach, Quarterly Journal of the Royal Meteorological Society, 128, pp. 1-20, 2002.

[8] A. Agarwal, J. Le Moigne, T. El-Ghazawi and J. Joiner, “Dimension reduction of AIRS Infrared (IR) Hyperspectral data,” 2004 IEEE International Geoscience and Remote Sensing Symposium, IGARSS’04, Anchorage, Alaska, September 20-24, 2004.