# Investigation of Predictor-based Schemes for Lossless Compression of 3D Hyperspectral Sounder Data

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*Abstract:* - Hyperspectral sounder data is used for retrieval of surface properties and atmospheric temperature, moisture, trace gases, clouds and aerosols. This large volume three-dimensional data is taken from many scan lines containing cross-track footprints, each with thousands of infrared channels. Unlike hyperspectral imager data compression, hyperspectral sounder data compression is better to be lossless or near lossless in order not to substantially degrade the geophysical retrieval. In this paper, we review different prediction-based schemes including CALIC and JPEG-LS for hyperspectral sounder data compression. To exploit the high spectral correlations, we also develop a method for optimal spectral prediction in the least square sense. A comparison with the JPEG2000 wavelet-based scheme is presented. The results show that the developed optimal prediction scheme outperforms all the other schemes in terms of compression ratios.

*Keywords:* - Lossless Compression, 3D Hyperspectral Sounder Data, JPEG-LS, CALIC, JPEG2000

## 1 Introduction

The advance of contemporary and future hyperspectral infrared sounders such as Atmospheric Infrared Sounder (AIRS) [1], Cross-track Infrared Sounder (CrIS) [2], Infrared Atmospheric Sounding Interferometer (IASI) [3], Geosynchronous Imaging Fourier Transform Spectrometer (GIFTS) [4], and, Hyperspectral Environmental Suite (HES) [5] has made better weather prediction and climate monitoring possible. The sounders generate an unprecedented amount of three-dimensional (3D) data that consists of two spatial and one spectral dimension. For example, the HES is the next-generation NOAA/NESDIS Geostationary Operational Environmental Satellite (GOES) hyperspectral sounder, slated to be launched in 2013. It would be either a Michelson interferometer or a grating spectrometer, with hyperspectral resolution (over one thousand infrared channels with spectral widths on the order of 0.5 wavenumber), high temporal resolution (better than 1 hour), high spatial resolution (less than 10km) and hemispheric coverage. Given the large volume of 3D data that will be generated by a hyperspectral sounder each day, the use of robust data compression techniques will be beneficial to data transfer and archive.

CALIC [6], JPEG-LS [7], and JPEG2000 [8] are the state-of-the-art compression algorithms but they only support compression of 2D data. To improve the compression gains of these state-of-the-art 2D compression algorithms on the hyperspectral sounder data, we have implemented a mean-removed nearest neighbor reordering (MR-NNR) scheme to convert the 3D data into 2D with the highest correlation channels rearranged together [9]. Furthermore, we develop a technique for optimal prediction of individual channels of the 3D data set via least-squares (LS) optimization.

The rest of the paper is arranged as follows. Section 2 describes the hyperspectral sounder data used in this study. Section 4 elaborates the optimal prediction algorithm. The compression results are presented in Section 5 while Section 6 concludes the paper.

## 2 Hyperspectral Sounder Data

As previously mentioned, the hyperspectral sounder data could be generated from either a Michelson interferometer (e.g. CrIS, IASI and GIFTS) or a grating spectrometer (e.g. AIRS). In this paper we have adopted the NASA AIRS radiance observations on Sept. 6, 2002. The AIRS data 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 granules, each of 6 minute durations. Each granule consists of 135 scan lines containing 90 cross-track footprints per scan line; thus there are a total of 135 x 90 = 12,150 footprints per granule. The 16-bit raw radiances are converted into the brightness temperatures, and then scaled as unsigned 16-bit integers. To make the selected data more generic to other hyperspectral sounders, 270 bad channels identified in the supplied AIRS infrared channel properties file are excluded, assuming that they occur only in the AIRS sounder. Each resulting granule is saved as a binary file, arranged as 2108 channels, 135 scan lines, and 90 pixels for each scan line.

For this hyperspectral sounder data compression study, ten granules, five daytime and five nighttime, are selected from representative geographical regions of the Earth. Their locations, UTC times and local time adjustments are listed in Table 1. The data is available via anonymous ftp [10]. More information regarding the AIRS instrument may be acquired from the NASA AIRS website [11]. Fig. 1 shows the AIRS radiances at wavenumber 900.3cm$^{-1}$ for the 10 selected granules on Sept. 6, 2002. In these granules, coast lines are depicted by solid curves and multiple clouds at various altitudes are shown as different shades of colored pixels.

## 3 Inter-Channel Prediction using Least Squares Optimization

Least squares based adaptive prediction schemes have long been studied in literature for compression of image data [12][13][14]. The general idea of LS prediction is to represent a pixel as the linear combination of a set of pixels. For hyperspectral sounder data, the spectral correlation is generally much stronger than the spatial correlation. Therefore, for any given pixel, we chose its predictors to be the pixels in the same spatial location at different channels. The 3D hyperspectral data cube of size $n_c$ by $n_x$ by $n_y$ is reshaped into a 2D data set of size $n_c$ channels by $n_s$ pixels, where $n_s = n_x \times n_y$. Thus the $n_c$ vectors, each with $n_s$ pixels, are to be predicted. The problem can be formulated as computing a prediction estimate for a given pixel $x_{c,i}, c \in \{1,...,n_c\}\ i \in \{1,...,n_s\}$ from pixels at the same spatial location in *N* different channels:

$$\hat{x}_{c,i} = \sum_{k=1}^{N} \alpha_k \, x_{P_{c,k},i} \qquad (1)$$

where $\alpha_k, k = 1,\ldots,N$ are the coefficients of the predictor channels, $P_{c,k}$ denotes the *kth* predictor channel for the current channel *c*, and $\hat{x}_{c,i}$ is the prediction estimate for pixel $x_{c,i}$. The prediction coefficients are calculated using the closed-form solution of the LS optimization problem:

$$\mathrm{A} = (C^T C)^{\#} (C^T Y) \qquad (2)$$

where

$$C = \begin{bmatrix} x_{P_{c,1},1} & \cdots & x_{P_{c,N},1} \\ \vdots & \ddots & \vdots \\ x_{P_{c,1},n_s} & \cdots & x_{P_{c,N},n_s} \end{bmatrix} \quad Y = \begin{bmatrix} x_{P_{c,k},1} \\ \vdots \\ x_{P_{c,k},n_s} \end{bmatrix}$$

and $Z^{\#}$ represents the pseudo-inverse of $Z$, which deals with the case of the matrix being ill-conditioned [15].

The difference between the original channel vector and its predicted counterpart is then calculated. For lossless compression, these residual errors are entropy coded. The coefficients are reduced to 16-bit resolution and sent to the decoder as side information.

The predictor channels $P_{c,k}, k = 1,..., N$ are yet to be determined. Consider the degenerate case of linear prediction of a single vector $Y = \alpha X_1$. From the orthogonality principle, we know that the minimum error vector $E$ is orthogonal to $X_1$ and that $\|E\|$ is the minimum error obtained. This distance $\|E\|$ is related to the sine of the angle between the vectors $Y$ and $X_1$. Hence, the sine of the angle between the prediction and predicted channel will dictate the error obtained via LS optimization. Therefore, the object is to find the *N* channels with the smallest sine of their angles for any given predicted channel. Specifically, a matrix *D* is formed which contains the error distances, where *D(i,j)* is the distance between normalized vectors $\tilde{X}_i$ and $\tilde{X}_j$

$$D(i, j) = \left[1 - (\tilde{X}_i' \cdot \tilde{X}_j)^2\right]^{1/2} \qquad (3)$$

The *N* predictors for a predicted channel are determined using the matrix *D* by finding the lowest *N* error distances from the predicted channel. It is possible to use the same channel in predicting two or more channels. After least-squares optimization, the residual error channels are entropy coded using an adaptive arithmetic coder [16]. If for certain channels, the original entropy is smaller than the residual entropy, the original channels are encoded.

## 4 Results

The ten 3D AIRS granules mentioned in section 2 are studied in this paper for lossless hyperspectral sounder data compression. Each granule with the size of 2108 channels by 135 scan lines by 90 footprints is converted into 2D with the size of 2108 channels by 12150 samples via a horizontal zigzag scan. The MR-NNR scheme is then applied to the 2D granule along the spectral and/or spatial dimension, followed by encoding with the CALIC, JPEG-LS or JPEG2000 schemes. The compression results are represented in terms of compression ratios in Fig. 2. As seen in Fig. 2(a)-(c), all the compression algorithms combining reordering schemes and either the CALIC, JPEG-LS, or JPEG2000 outperform the CALIC, JPEG-LS, and JPEG2000 compression alone. Moreover, MR-NNR in the spectral dimension yields significantly better results than its counterpart in the spatial dimension.

The compression ratios for the proposed Inter-channel prediction scheme are shown in Table 2 for $N$=32 predictors. These are compared with the compression ratios obtained by combining the best MR-NNR with CALIC, JPEG-LS and JPEG2000. The proposed method on average produces 10.79%, 10.76% and 10.8% higher compression ratios than the ratios for CALIC, JPEG-LS and JPEG2000. This demonstrates the viability of using LS optimization based prediction for hyperspectral sounder data.

## 5 Conclusion

A new predictor-based scheme for hyperspectral sounder data is proposed that produces better results than our previous work with the MR-NNR scheme. The choice of the distance matrix is geared towards providing minimum residual errors. Future work includes the research into selection of optimal predictor vectors.

## Acknowledgement

The authors would like to thank Dr. Elisabeth Weisz for providing the original AIRS data. This research is supported by National Oceanic and Atmospheric Administration's National Environmental Satellite, Data, and Information Service under grant NA07EC0676. The views, opinions, and findings contained in this report are those of the author(s) and should not be construed as an official National Oceanic and Atmospheric Administration or U.S. Government position, policy, or decision.

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| | | | |
|---|---|---|---|
| Granule 9 | 00:53:31 UTC | -12 H | (Pacific Ocean, Daytime) |
| Granule 16 | 01:35:31 UTC | +2 H | (Europe, Nighttime) |
| Granule 60 | 05:59:31 UTC | +7 H | (Asia, Daytime) |
| Granule 82 | 08:11:31 UTC | -5 H | (North America, Nighttime) |
| Granule 120 | 11:59:31 UTC | -10 H | (Antarctica, Nighttime) |
| Granule 126 | 12:35:31 UTC | -0 H | (Africa, Daytime) |
| Granule 129 | 12:53:31 UTC | -2 H | (Arctic, Daytime) |
| Granule 151 | 15:05:31 UTC | +11 H | (Australia, Nighttime) |
| Granule 182 | 18:11:31 UTC | +8 H | (Asia, Nighttime) |
| Granule 193 | 19:17:31 UTC | -7 H | (North America, Daytime) |

Table 1. Ten selected AIRS granules for hyperspectral sounding data compression studies.

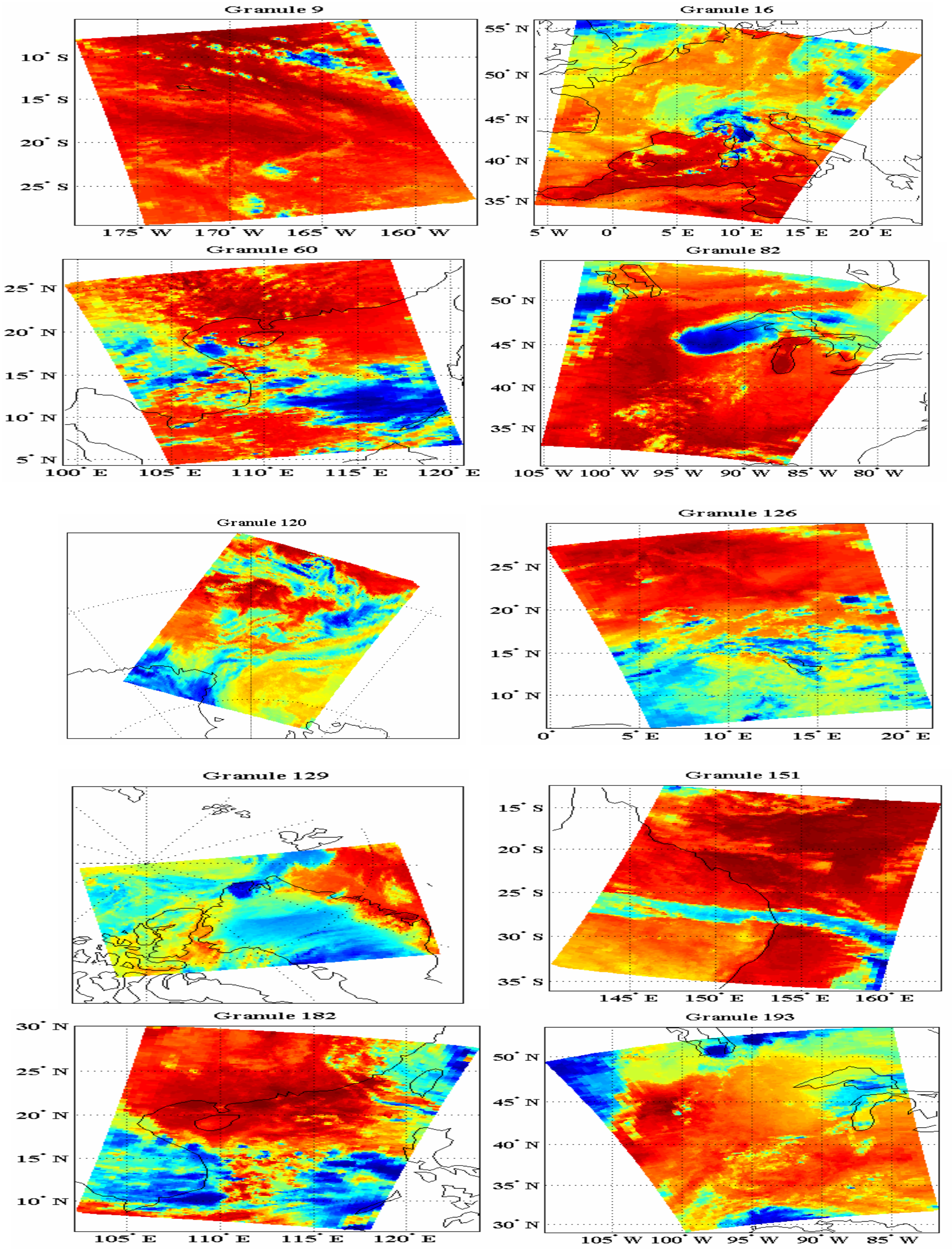
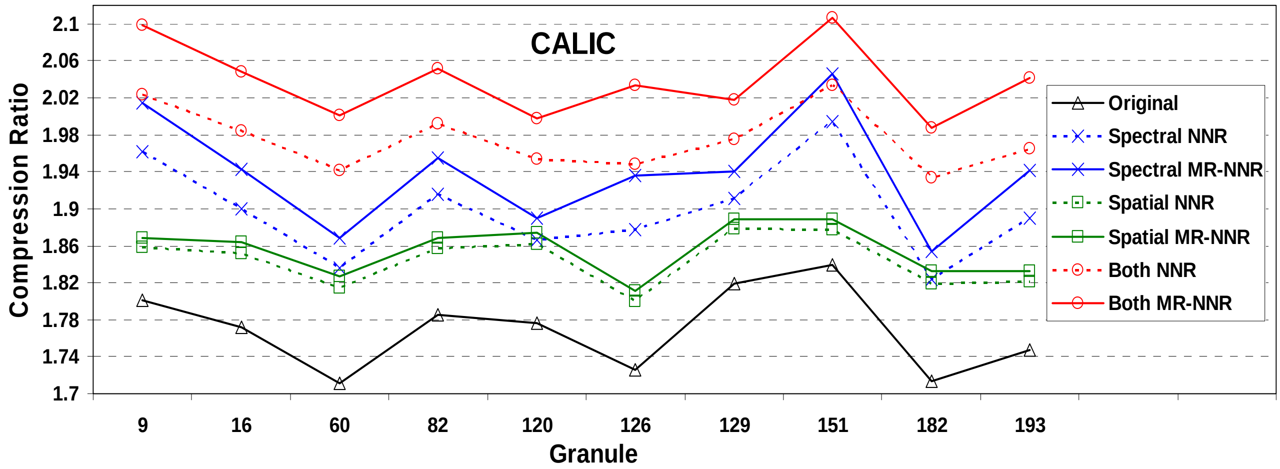
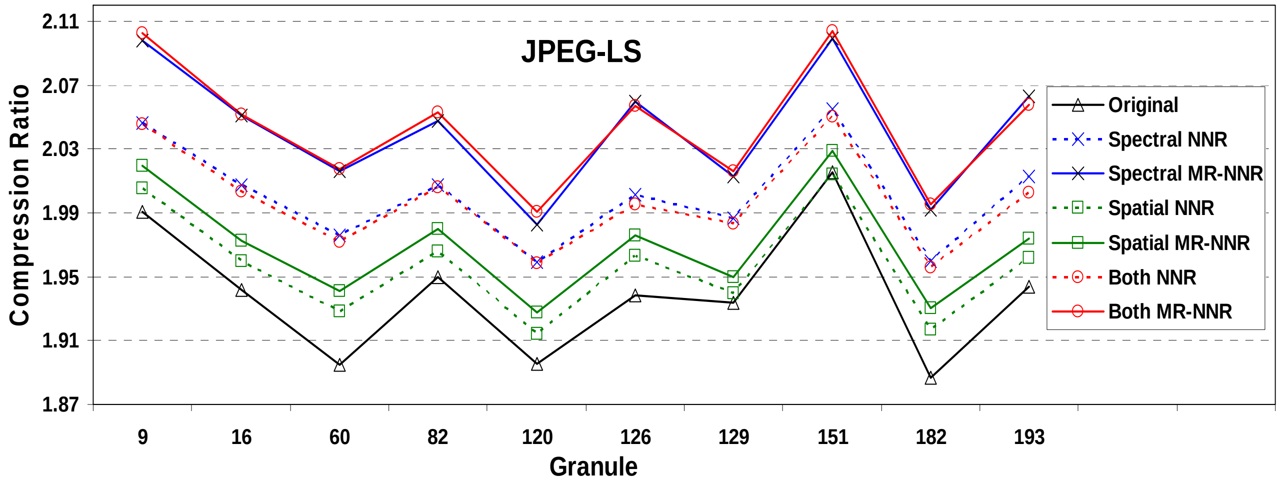


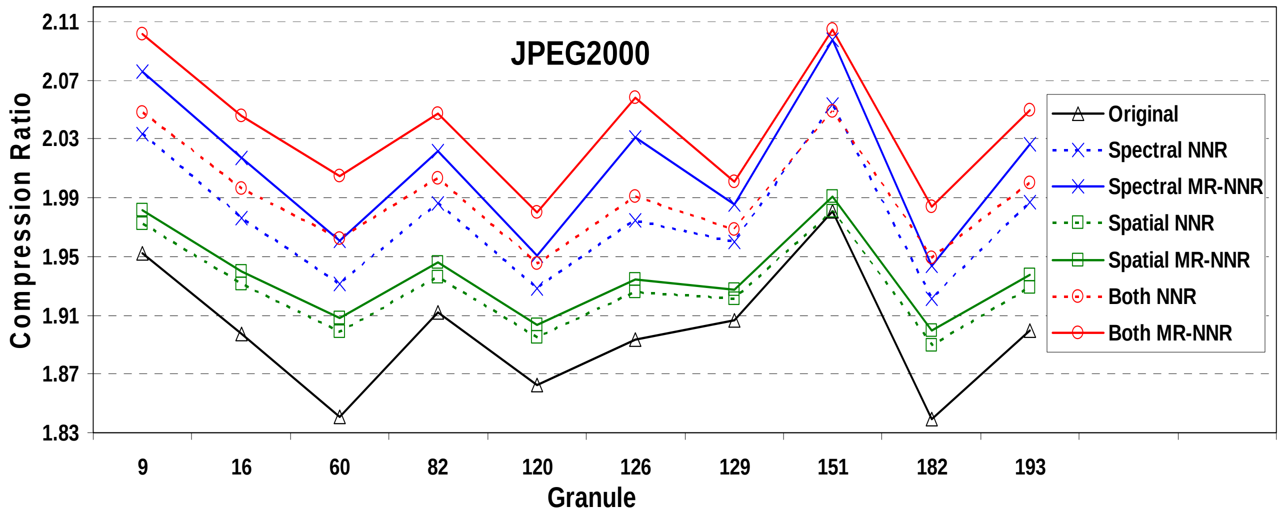

Fig. 1. Spatial distribution of AIRS radiance at wavenumber 900.3cm$^{-1}$ for the 10 selected granules on Sept. 6, 2002.




(a)




(b)




(c)

Fig. 2 (a) Compression ratios for CALIC with and without various reordering schemes for all the 10 tested granules. (b) Same as (a) except for JPEG-LS. (c) Same as (a) except for JPEG2000.

| Granule | Both MR-NNR CALIC | Both MR-NNR JPEG-LS | Both MR-NNR JPEG2000 | Proposed |
|---|---|---|---|---|
| 9 | 2.099 | 2.103 | 2.102 | 2.306 |
| 16 | 2.048 | 2.052 | 2.045 | 2.139 |
| 60 | 2.001 | 2.018 | 2.005 | 2.200 |
| 82 | 2.052 | 2.053 | 2.047 | 2.138 |
| 120 | 1.998 | 1.991 | 1.980 | 2.135 |
| 126 | 2.033 | 2.057 | 2.058 | 2.304 |
| 129 | 2.018 | 2.016 | 2.001 | 2.168 |
| 151 | 2.107 | 2.104 | 2.105 | 2.284 |
| 182 | 1.988 | 1.996 | 1.984 | 2.105 |
| 193 | 2.041 | 2.058 | 2.050 | 2.240 |
| Average | **2.039** | **2.045** | **2.038** | **2.202** |

Table 2. Compression ratios for the proposed scheme using 10 tested granules