Mean-removed Nearest Neighbor Reordering Based Lossless Compression of 3D Hyperspectral Sounder Data

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Abstract: - Hyperspectral sounder data is used for retrieval of atmospheric temperature, moisture and trace gases profiles, surface temperature and emissivity, cloud and aerosol optical properties. The physical retrieval of these geophysical parameters is a mathematically ill-posed problem whose solution is sensitive to the error or noise in the data. Therefore, lossless or near lossless compression of hyperspectral sounder data is desired to avoid potential retrieval degradation of the geophysical parameters. In addition to the spatial correlations of observed nature scenes, the hyperspectral sounder data features high correlations in disjoint spectral regions affected by the same type of absorbing gases. A preprocessing scheme to explore the spectral and spatial correlations will be beneficial for compression gains. In this paper we investigate Mean-removed Nearest Neighbor Reordering (MR-NNR) for preprocessing the sounder data. The result is then encoded using state-of-the-art compression algorithms such as CALIC, JPEG-LS and JPEG2000. It is shown that by use of the MR-NNR scheme, the compression gains of CALIC, JPEG-LS and JPEG2000 increase up to 15%, 5% and 7% respectively over the original data without any preprocessing.

Key Words: - Lossless Compression, 3D Hyperspectral Sounder Data, NNR, 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 replace the current 18-band GOES sounder 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.

There is a difference between hyperspectral *sounder* and *imager* data. The hyperspectral *imager* data (e.g. the well-known AVIRIS data [6],[7]) is in the visible or near-infrared regions with the main purpose of pattern recognition and classification where significant data loss from lossy compression is usually acceptable is usually acceptable due to limited visual perception of the human visual system (HVS). On the other hand, the hyperspectral *sounder* data is in the infrared region with the main purpose of retrieving atmospheric temperature, moisture and trace gases profiles, surface temperature and emissivity, cloud and aerosol optical properties for better weather and climate prediction. Physical retrieval of these geophysical parameters involves the inverse solution of the radiative transfer equation and it is a mathematically ill-posed problem [8], i.e. the solution is sensitive to the error or noise in the data. For example, the observed signal-to-noise ratios in the AIRS infrared longwave channels can be over 400 in the clear sky cases, implying that the allowable reconstructed error is lower than the smallest error visually perceptible by the HVS. Therefore there is a need for lossless or near-lossless compression of hyperspectral sounder data to avoid potential retrieval degradation of geophysical parameters due to lossy compression.

CALIC [9], JPEG-LS [10], and JPEG2000 [11] are the state-of-the-art compression algorithms but they only support compression of 2D data. To apply these algorithms to the 3D hyperspectral sounder data, one can process the data framewise or make the data two-dimensional by converting the two spatial dimensions into one dimension via a continuous scan. The disadvantage to the first approach is that it does not explore the correlation between different spectral channels. The second approach is a better alternative for exploring the correlation among neighboring channels via the local predictor techniques (JPEG-LS, CALIC) or the wavelet transform (JPEG2000), but it does not explore the correlation among distant channels – an important feature in the hyperspectral sounder data. To improve the compression gains of these state-of-the-art 2D compression algorithms on the hyperspectral sounder data, we implement a mean-removed nearest neighbor reordering (MR-NNR) scheme to convert the 3D data into 2D with the highest correlation channels rearranged together.

This MR-NNR scheme takes advantage of the unique spectroscopic characteristic of the hyper-spectral sounder data that features high correlations in disjoint spectral regions affected by the same type of absorbing gases. It can also explore the spatial correlations of disjoint geographical regions affected by the same type of absorbing gases or clouds. It is geared towards exploiting these correlations along different dimensions.

The rest of the paper is arranged as follows. Section 2 describes the hyperspectral sounder data used in this study. Section 3 highlights the compression schemes used, while Section 4 elaborates the MR-NNR algorithm. The compression results with and without the MR-NNR scheme are presented in Section 5. 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 instrument aboard NASA's Aqua spacecraft employs a 49.5 degree cross-track scanning with a 1.1 degree instantaneous field of view to provide twice daily coverage of essentially the entire globe in a 1:30 PM sun synchronous orbit. 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 [12]. More information regarding the AIRS instrument may be acquired from the NASA AIRS website [13]. 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 Compression Schemes

CALIC, JPEG-LS and JPEG2000 are the state-of-the-art lossless compression schemes that are studied in the paper. CALIC and JPEG-LS utilize neighboring pixels to predict the current pixel, followed by entropy coding of the prediction errors. JPEG2000 performs a wavelet transform on the pixels followed by block coding.

3.1 CALIC

The CALIC scheme is considered as the most efficient and complex encoder for compression of 2D continuous-tone images. Among the nine proposals in the initial ISO/JPEG evaluation in July 1995, CALIC was ranked first. It works on the principle of a context-adaptive non-linear predictor which adjusts to the local gradients around the current pixel. The algorithm operates in the binary or continuous modes. The binary mode codes the regions of the image in which the intensity value is no more than two. In the continuous mode, the system has four major components: gradient-adjusted prediction, context selection and quanti-zation, context modeling of prediction errors, and entropy coding of prediction errors.

3.2 JPEG-LS

The ISO/IEC working group released a new standard for the lossless/ near lossless compression of continuous-tone images in 1999, popularly known as JPEG-LS. It features low complexities based on predictive coding technique. Near lossless compression is controlled through an integer valued threshold representing the maximum permissible absolute difference between each original pixel value and its decompressed value. The JPEG-LS encoder is composed of four main stages: prediction, context modeling, error encoding, and run mode.

3.3 JPEG2000

Unlike CALIC or JPEG-LS, JPEG2000 is the state-of-the-art compression algorithm for 2D still images based on wavelet transforms. It is published as a standard of the International Organization for Standardization/International Electrotechnical Commission (ISO/IEC), as well as an International Telecommunications Union-Terminal Sector (ITU-T) Recommendation. It is intended to replace the previous ISO/IEC standard, JPEG, which is based on discrete cosine transforms. It features progressive transmission by quality, resolution, component, or spatial locality, lossy and lossless compression, region of interest coding by progression, and limited memory implementations, to name a few.

4 Mean-removed Nearest Neighbor Reordering

Consider a 3D hyperspectral data cube of size n_c by n_x by n_y. For CALIC, JPEG-LS and JPEG2000 compression, the data is reshaped into a 2D data of size n_c by n_s via a continuous zigzag scan, where $n_s = n_x \times n_y$. When data is spectrally reordered, there are n_c vectors, each with n_s components. The mean is removed and rounded from each of the n_c vectors. Let S be the pool of the mean-removed vectors not yet reordered. In the MR-NNR scheme along the spectral dimension we start with a reference vector, and each vector $V \in S$ is compared with the reference vector. The best matched vector is the nearest neighbor of the reference vector. It then becomes a new reference vector and is removed from S. The process is repeated until the pool S becomes empty. Mathematically, given the *i-th* reordered vector $\tilde{V}^i$, we are seeking V^*, the minimum norm solution of

$$\min_{V \in S} f^i(V),$$

where

$$f^i(V) = \left\| \tilde{V}^i - V \right\|.$$

Then the $(i+1)$*-th* reordered vector is simply $\tilde{V}^{i+1} = V^*$.

The minimum norm solution V^* can be found via exhaustive comparisons of all the vectors V in S with $\tilde{V}^i$ for the nearest neighbor. This approach has a complexity of $O(n_s^2)$. A faster approach with an $O(n_s)$ complexity can be obtained via a linear sort of all the vectors in S based on their rounded absolute distances, and then only comparing m nearest neighbors around the reference vector. The actual nearest neighbor is found when the constant m is large enough but still much smaller than n_s.

5 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. Table 2(a)-(c) show the achieved bit rates in bits per pixels for all the granules compressed using the three different encoders. For all the three tables, column 2 shows the compression result without any data reordering; columns 3, 5, and 7 are the results for the NNR scheme without mean removal along the spectral, spatial and both dimensions, respectively; whereas columns 4, 6, and 8 are for MR-NNR along spectral, spatial and both dimensions, respectively.

Alternatively, the compression results can be represented in terms of compression ratios as illustrated 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 significantly outperform the CALIC, JPEG-LS, and JPEG2000 compression alone. Also, the results from the NNR with mean removal is much better than the plain NNR without mean removal. Moreover, MR-NNR in the spectral dimension yields significantly better results than its counterpart in the spatial dimension. CALIC has a 9.6% average improvement for spectral MR-NNR over its original compression ratio; for JPEG-LS and JPEG2000 these values are 5.3% and 5.9% respectively. In case of spatial MR-NNR, the average percentage improvements for the ten granules drop down to 4.9%, 1.6%, and 2% for CALIC, JPEG-LS, and JPEG2000 respectively. This illustrates that better compression gains can be obtained by reordering correlated channels from disjoint spectral regions than by reordering correlated pixels from disjoint spatial regions. Fig. 3 shows the sorting indices plotted against the original indices in the cases of spectral NNR and spectral MR-NNR for 3 granules. The sorting indices are quite different from the original indices as judged by their great deviation from the straight line. This shows the natural channel order given by the spectral wavelengths do not possess optimal correlation in neighboring channels. Since there is compression gain along each dimension, the reordering along both dimensions outperforms their reordering counterparts along the spectral or spatial dimension alone for most of the granules. Specifically, the average improvements for both MR-NNR are 15.2%, 5.4%, and 7.3% for CALIC, JPEG-LS and JPEG2000 respectively.

6 Conclusion

The hyperspectral sounder data is a new class of 3D data for compression studies. The compression of this data is better to be lossless or near lossless to avoid significant degradation of the geophysical retrieval. In this paper lossless compression of the 3D hyperspectral sounder data is performed using state-of-the-art compression schemes with MR-NNR reordering. A comparison of the compression results for CALIC, JPEG-LS and JPEG2000 are given. The results show that MR-NNR outperforms the compression schemes without reordering in terms of compression ratios for the ten granules of the AIRS hyperspectral data representing different geographical locations of the earth.

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[13] http://www-airs.jpl.nasa.gov

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.

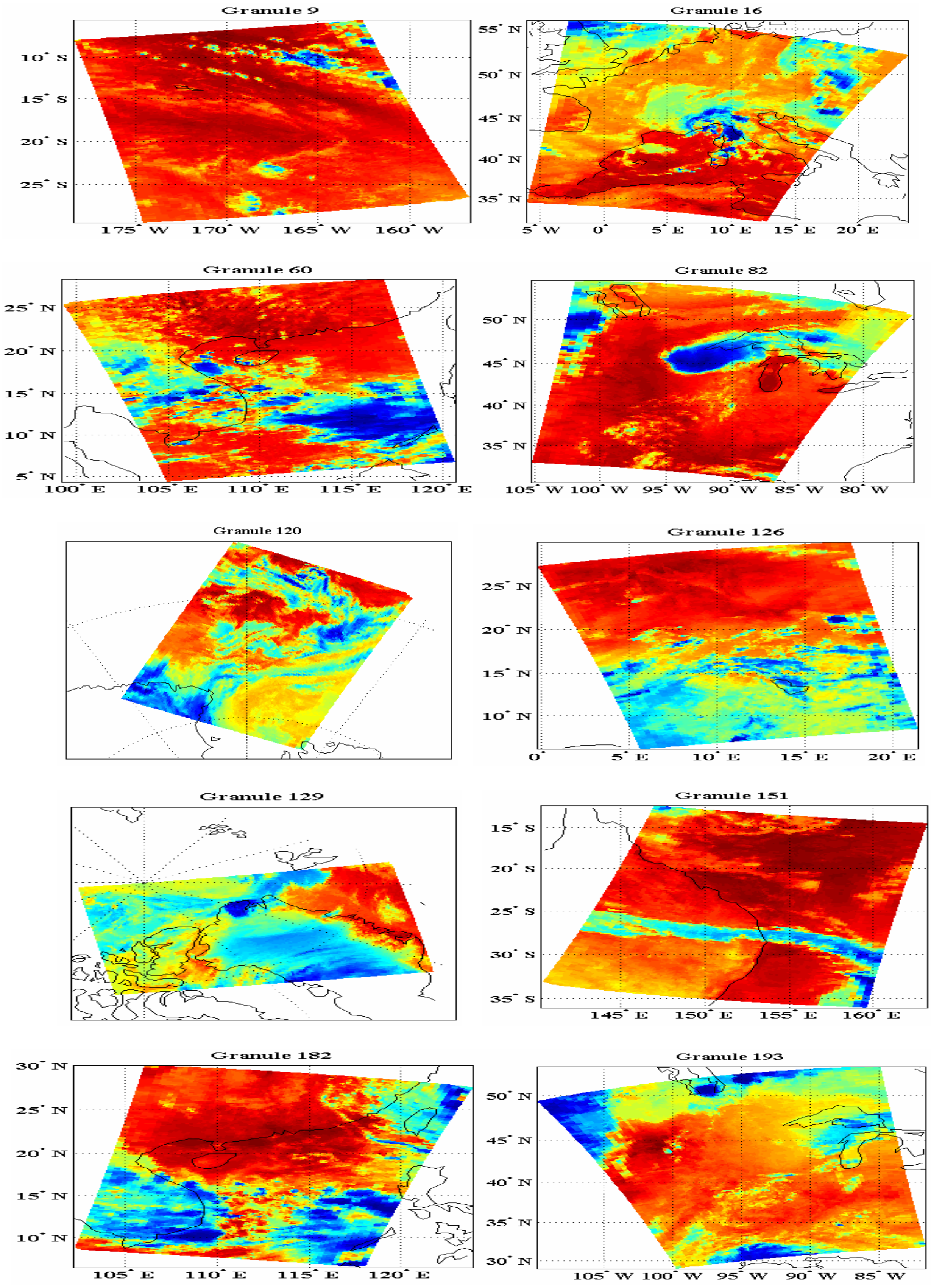


Fig. 1. Spatial distribution of AIRS radiance at wavenumber 900.3cm^{-1} for the 10 selected granules on Sept. 6, 2002.

Granule No.	Original	Spectral NNR	Spectral MR-NNR	Spatial NNR	Spatial MR-NNR	Both NNR	Both MR-NNR
9	8.8840	8.1587	7.9436	8.6072	8.5630	7.9063	7.6227
16	9.0309	8.4193	8.2372	8.6398	8.5865	8.0661	7.8121
60	9.3529	8.7170	8.5607	8.8164	8.7590	8.2398	7.9952
82	8.9631	8.3529	8.1867	8.6170	8.5612	8.0341	7.7977
120	9.0065	8.5745	8.4643	8.5952	8.5370	8.1888	8.0084
126	9.2700	8.5247	8.2670	8.8874	8.8359	8.2123	7.8698
129	8.7985	8.3700	8.2474	8.5174	8.4723	8.0992	7.9290
151	8.6990	8.0229	7.8194	8.5206	8.4705	7.8698	7.5952
182	9.3403	8.7724	8.6291	8.7941	8.7293	8.2764	8.0491
193	9.1554	8.4643	8.2427	8.7840	8.7298	8.1404	7.8393
Average	9.0500	8.4377	8.2598	8.6779	8.6244	8.1033	7.8518

(a)

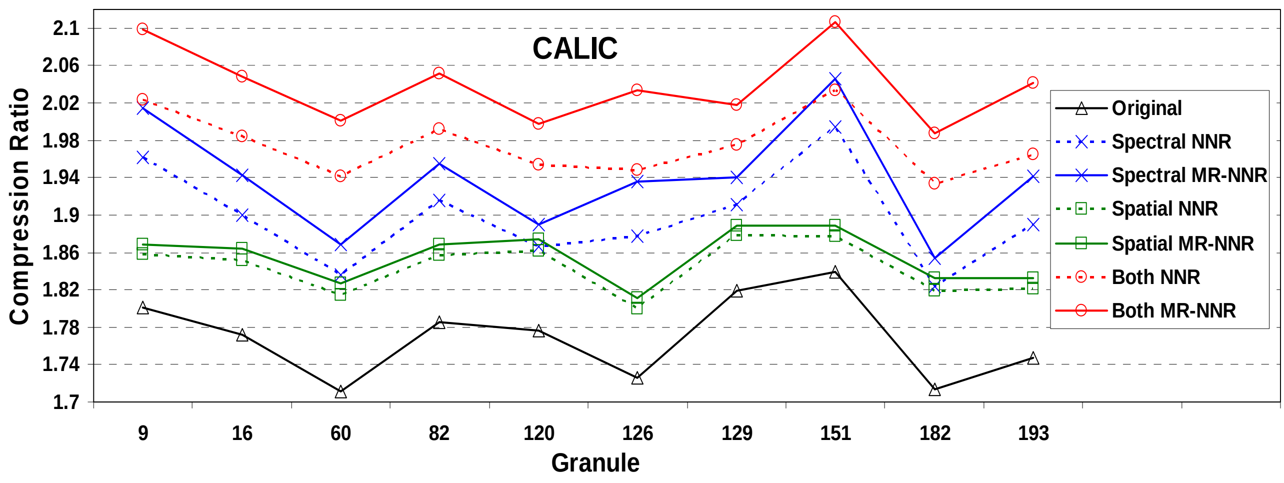
Granule No.	Original	Spectral NNR	Spectral MR-NNR	Spatial NNR	Spatial MR-NNR	Both NNR	Both MR-NNR
9	8.0386	7.8178	7.6274	7.9777	7.9231	7.8205	7.6096
16	8.2394	7.9697	7.8015	8.1649	8.1107	7.9868	7.7980
60	8.4442	8.0972	7.9357	8.2966	8.2427	8.1136	7.9298
82	8.2072	7.9709	7.8136	8.1392	8.0808	7.9769	7.7942
120	8.4406	8.1670	8.0698	8.3581	8.3000	8.1691	8.0374
126	8.2538	7.9956	7.7677	8.1508	8.0963	8.0192	7.7791
129	8.2739	8.0548	7.9503	8.2474	8.2072	8.0678	7.9365
151	7.9397	7.7851	7.6209	7.9452	7.8864	7.8034	7.6046
182	8.4795	8.1649	8.0333	8.3481	8.2876	8.1804	8.0180
193	8.2305	7.9499	7.7553	8.1562	8.1054	7.9884	7.7764
Average	8.2547	7.9973	7.8376	8.1784	8.1240	8.0126	7.8284

(b)

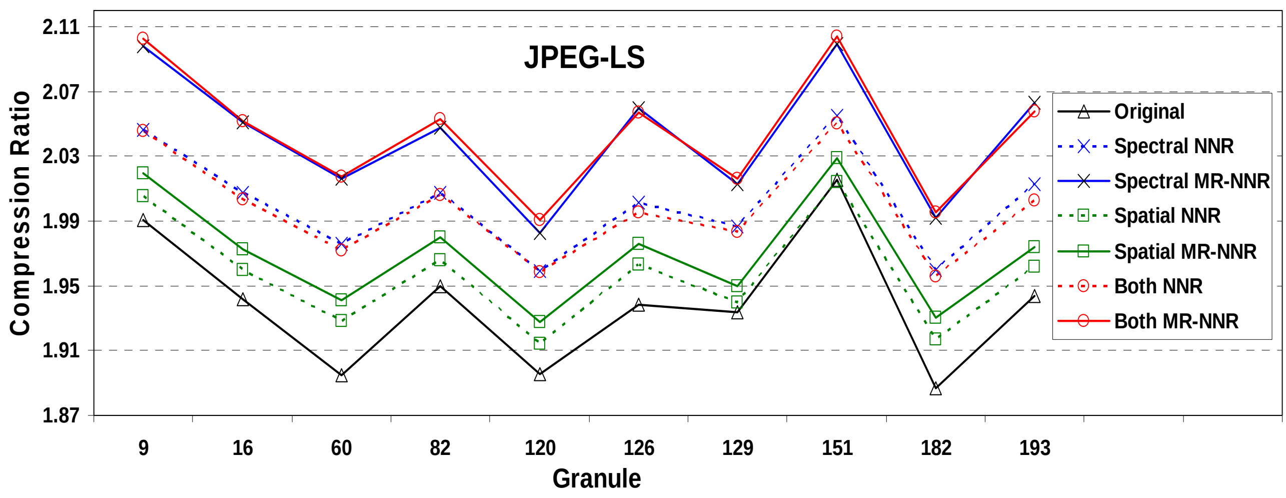
Granule No.	Original	Spectral NNR	Spectral MR-NNR	Spatial NNR	Spatial MR-NNR	Both NNR	Both MR-NNR
9	8.1971	7.8682	7.7082	8.1136	8.0755	7.8136	7.6125
16	8.4348	8.0951	7.9326	8.2854	8.2487	8.0164	7.8224
60	8.6900	8.2859	8.1604	8.4273	8.3866	8.1525	7.9804
82	8.3695	8.0568	7.9145	8.2636	8.2207	7.9880	7.8152
120	8.5906	8.2992	8.2034	8.4446	8.4042	8.2254	8.0808
126	8.4513	8.1025	7.8763	8.3082	8.2704	8.0370	7.7742
129	8.3932	8.1620	8.0576	8.3268	8.3009	8.1272	7.9952
151	8.0780	7.7923	7.6278	8.0775	8.0354	7.8102	7.6017
182	8.6994	8.3294	8.2334	8.4665	8.4215	8.2077	8.0661
193	8.4224	8.0536	7.8958	8.2949	8.2589	8.0008	7.8068
Average	8.4326	8.1045	7.9610	8.3008	8.2623	8.0379	7.8555

(c)

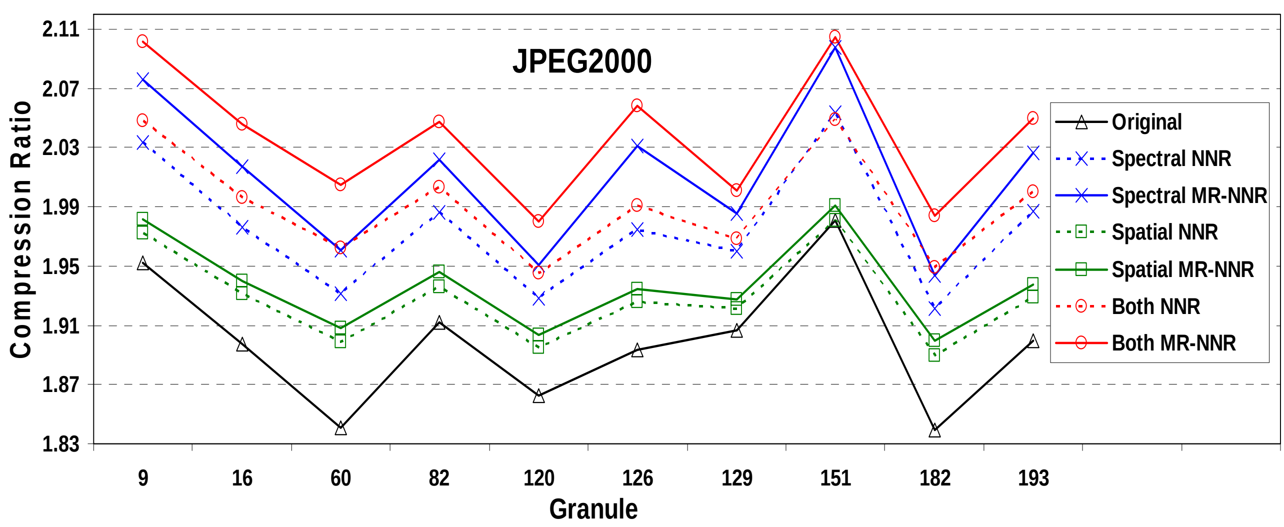
Table 2 (a)-(c) Bit rates for the 10 granules in bits per pixels with and without various reordering schemes for CALIC, JPEG-LS and JPEG2000, respectively.



(a)

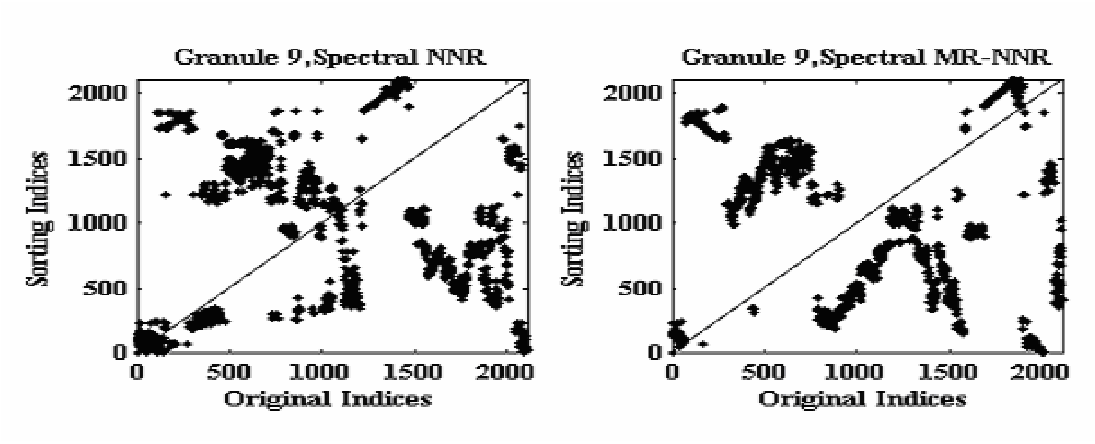


(b)

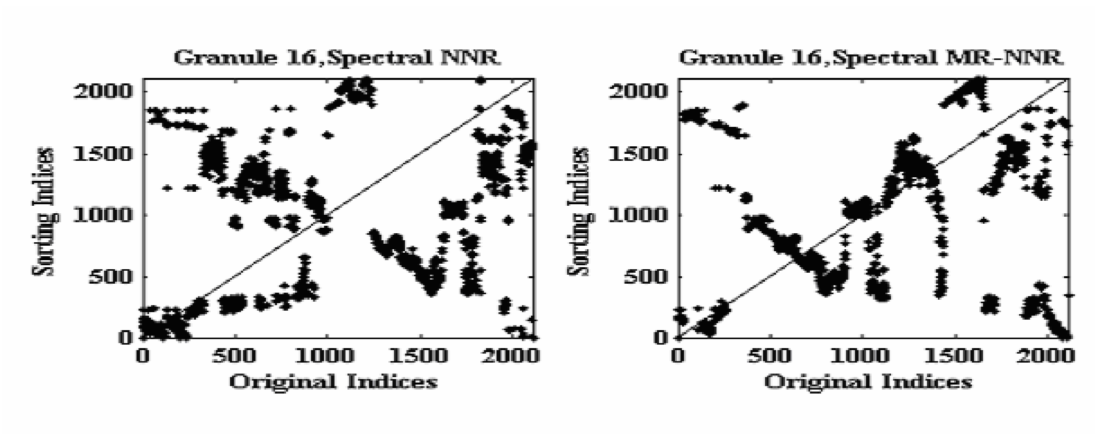


(c)

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.



(a)



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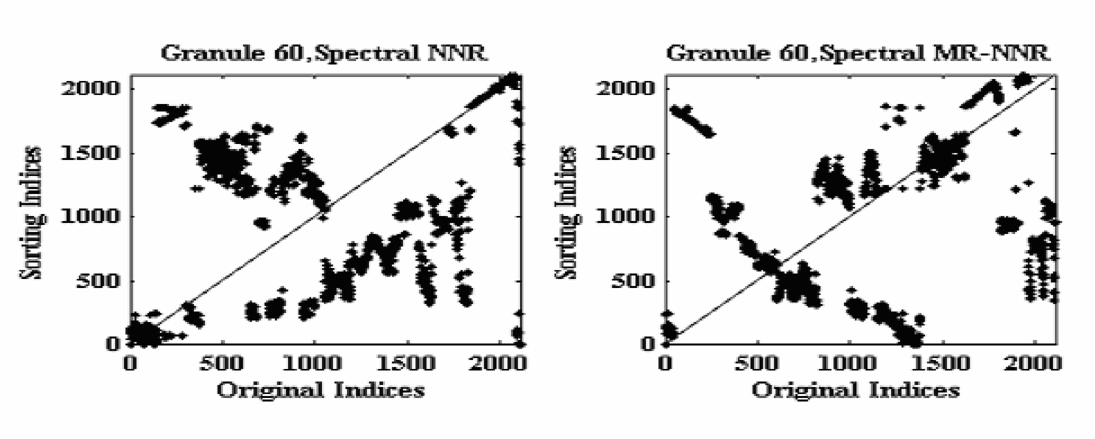

(c)

Fig. 3 (a) Granule 9 Sorting indices for Spectral NNR and Spectral MR-NNR (b) Same as (a) except for Granule 16. (c) Same as (a) except for Granule 60.