

The impact of striping artifacts on compression

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ABSTRACT

Despite tremendous efforts to avoid them, stripes are a re-occurring problem for many remote imaging sensors. Much work has focused on suppressing or eliminating them in order to recover accurate observed radiances. Beyond the obvious need to eliminate stripes to obtain accurate scientific measurements, stripes can also significantly impact the performance of compression algorithms. Many compression algorithms are based on linear representations of image space or assume the data to be relatively smooth. In contrast stripes produce non-linearities in the data as well as sharp discontinuities which make it seem necessary to describe the images with many parameters. Yet the sources and nature of the stripes are often not well known, they could come from specific irregularities with the sensors. If the *a priori* construction of the sensor is accounted for, and the stripe statistically modeled, it is possible to transmit the stripe parameters separately along with de-striped images. The de-striped images have image statistics whose assumptions are much closer to those for which standard compression algorithms are optimized. As an example, we show this yields a significant boost in the performance of these algorithms when applied to the de-striped MODIS images.

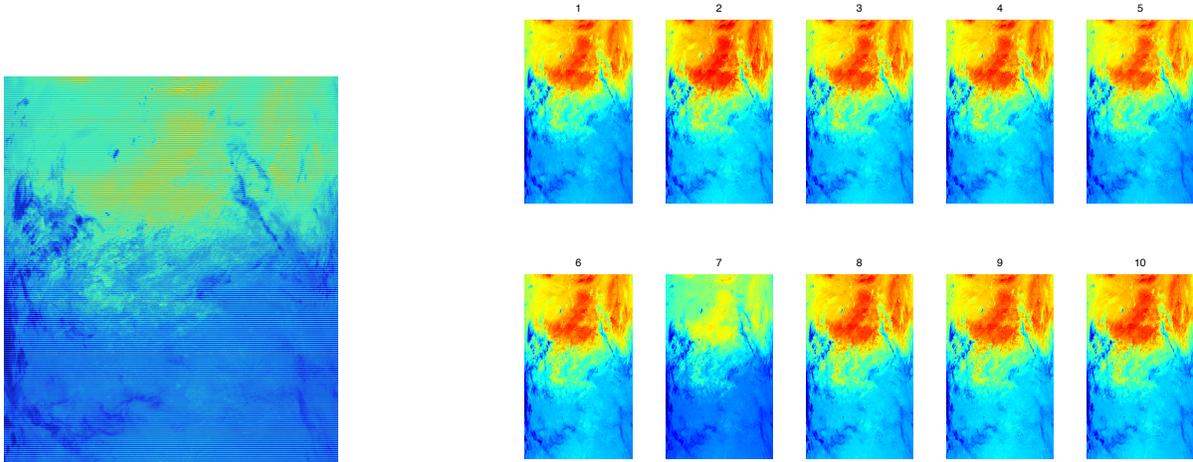
1. INTRODUCTION

The MODERate resolution Imaging Spectroradiometer (MODIS) is a key instrument aboard the Terra (EOS AM) and Aqua (EOS PM) polar satellites. Terra's orbit around the Earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. The MODIS instrument provides high radiometric sensitivity (12 bit) in 36 spectral bands ranging in wavelength from 0.4 μm to 14.4 μm . These 36 distinct spectral bands are divided into four separate Focal Plane Assemblies (FPA): Visible (VIS), Near Infrared (NIR), Short- and Mid-Wave Infrared (SWIR/MWIR), and Long-Wave Infrared (LWIR). Each FPA focuses light onto a certain section of detector pixels, which are relatively large, ranging from 135 μm to 540 μm square. The large number and variety of detector pixels are what make the wide variety of MODIS data possible. When light hits a detector pixel, it will generate a distinct signal depending on the type of light it is sensitive to. The signals that the pixels generate are what scientists process and study to learn about Earth's land surfaces, water surfaces, and atmosphere.

Striping is a well known impairment that affects the radiometric measurements of MODIS. It is due to the anomalous behavior of the input/output transfer function of the single detectors in the FPA. There are 10 detector elements along track for each of the 1 km bands, 20 for each of the 500 m bands, and 40 for the 250 m bands. In this paper we are particularly interested in the effects of de-striping on compression of the LWIR channels, bands 20-36, which have a bandwidth ranging from 3.7 μm to 14.4 μm and striping is more pronounced. These bands are primarily useful in the measurement of surface/cloud temperature, atmospheric temperature, cirrus cloud water vapor, cloud properties, ozone, and cloud top altitude.

De-striping methods that can be found in the literature on de-striping hyper-spectral satellite images, like GOES series, MODIS Terra/Aqua imagers, are geared towards calibration of the data. Traditionally noise is treated by means of convolution techniques using digital filters.¹ Unfortunately these techniques sensor independent and lead to blurring of the original image. These filters not only suppress the spatial frequency components of the stripe but also the information content of the image. Moment matching methods have also been applied to the de-striping problem. These methods depend on the assumption that the mean and the standard deviation do not vary across different sensor data.² This assumption, however, does not hold true for MODIS imager data.

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(a) Channel 2 (2030×1354)

(b) 10 sensor images (203×1354)

Figure 1. a) Is an example of an image with stripes from the EV_1km_night case (channel 2). b) It shows the 10 images one for each sensor. These images look very smooth but when put together to get a), the stripes are quite pronounced

Histogram matching method assumes that the probability distribution of the scene radiance measured by each image sensor is the same.³ The measured values of the sensors are then mapped so that they take values in a common domain. This domain could be scene radiance or the simply to one of the sensors. In,³ the authors perform this modification by taking the statistics of whole image.

Our proposal is that the de-stripping of multi-spectral images is useful for compression. The idea is that stripes introduce high frequency components which transform algorithms like JPEG-2000 must expend components to capture. A destriped image should, a-priori be smoother and thus require fewer and smaller high frequency components to compress. We have used state of the art compression software JPEG-2000 on de-striped images and found significant improvements in the compression ratio.

The paper is organized as follows: In section 2, we introduce statistical de-stripping techniques. In section 3, we briefly overview one of the eccentricities of the sensors which result in offsets in each sensors image. In section 4, we present our lossless compression algorithm with destripping as a preprocessing method.

2. DESTRIPIING ALGORITHMS

One method to destripe an image is through calibration. In calibrating the k sensors, k monotonic response curves $y = g_k(x)$ are determined, with x a digital count, and y a quantity linear in the energy falling on the sensor (irradiance). Further calibration is needed to turn y into a scene radiance. However, a representation of the irradiance is sufficient to create a destriped image. This is based on the physical assumption that the energy falls on the focal plane has no "stripes", the stripes being an artifact of the measurement processes.

Despite calibration being a principled approach it can have a number of drawbacks. A stripe may be present whenever two neighboring sensors consistently report even small differences in digital counts from one scan line to the next. If that change represent a difference of radiance within the acceptable radiance tolerance calibration may not correct it. Even if this has little impact on scientific measurements, this can make the image more difficult to compress.

By making statistical assumptions we can avoid the need for calibration in compression. In the next two subsections we present two closely related statistical methods: histogram specification and histogram equalization for destripping. Both rely on mapping the grey levels of an image to a set of grey levels by preserving the monotonicity property of the cumulative histograms each sensor.

2.1 Histogram specification

To begin with, each detector i sees a sub-image of the original image as seen in Figure 1. Not that these single-sensor images are essentially “stripe free.” The basic statistical assumption we make is that each of these images is a sampling from an identical distribution of scene radiance. This assumption relies partly on the fact that the images at 2030×1354 for the 1km MODIS bands, the images are sufficiently large to be statistically stable from one sensor image to the next.

We first compute the cumulative probability distributions $H_i(x)$ for each one-detector sub-images x , where $x \in \{0, \dots, 2^{12} - 1\}$. A reference detector $j \in \{1, \dots, 10\}$ is chosen, (in the case of MODIS LWIR there are 10 sensors) and a lookup table $g(x)$ is now constructed by applying the inverse of the function $H_j(x)$ to $H_k(x)$, $k \in \{1, \dots, j - 1, j + 1, \dots, 10\}$. This lookup table is then used to modify all the sensor values produced by each sensor $k \in \{1, \dots, j - 1, j + 1, \dots, 10\}$. The inverse can be calculated relatively easily since $H_j(x)$ is a monotonically nondecreasing function. Although the map would not be a 1-1 map, so its not exactly invertible. The lookup table value $g(x)$ is the smallest number x such that

$$H_j(x) \leq H_k(x) < H_j(x + 1), \quad (1)$$

where j is the reference sensor. This process is repeated for each sensor in turn, until all image values have been modified by the lookup table appropriate to the sensor with which they were measured. Figure 2 shows an example of image destriped using specification method. It also shows the residual image which is computed by first computing the restriped image applying the inverse look-up table on the destriped image and subtracting the restriped image from the original image. We have found that empirically, at most pixels of the residual image are zero although a small number where the value is non-zero. This is due to the fact that the look-up maps are not 1-1. Hence when we invert these maps we do not retrieve the original image. Only in special cases when the all the sensors have exactly the same number of unique grey values do the maps become invertible. Figure 3 shows the look-up tables and the cumulative probability distributions of the image in Figure 2.

2.2 Histogram equalization

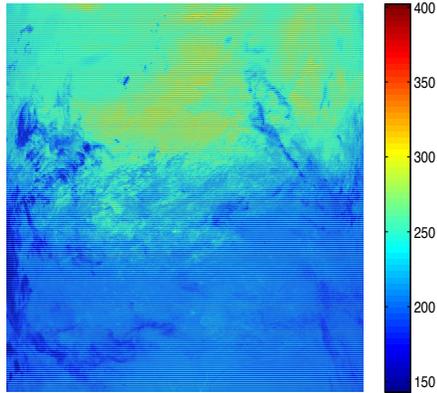
We first separate the image into k images, one for each sensor, by deinterlacing the stripes. In particular if a pixel from, for example, the first sensor $k = 1$ measures x_1 and from $k = 2$ measures x_2 and they correspond to the same irradiance if and only if $g_1(x_1) = y_0 = g_2(x_2)$. The image irradiance the sensor encounters is modeled at a pixel is modeled as a random variable Y with probability distribution p_Y . Because the overall (convex hull) of the field of view overlap, one expects that the probabilistic distribution of image irradiances should be nearly identical p_Y for the k images. Suppose y_0 is a given irradiance value. The proportion of total area of the image for which the irradiance at that pixel is less than y_0 is the cumulative probability density

$$P_Y(\leq y_0) = \int_0^{y_0} p_Y(Y) dY. \quad (2)$$

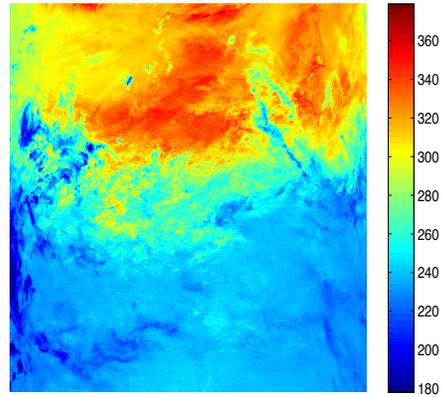
Because the response functions are monotonic, and we have assumed that the distributions for each sensor are the same, there is a value for each sensor x_1, x_2, \dots, x_k so that $P_{X_1}(\leq x_1) = \dots = P_{X_k}(\leq x_k) = P_Y(\leq y_0)$. The value $P_{X_i}(\leq x_i)$ is given by the cumulative histogram H :

$$P_{X_i}(\leq x_i) = H_i(x_i) * (1/N) = (1/N) \sum_{j=0}^{x_i} h_i(j) \quad (3)$$

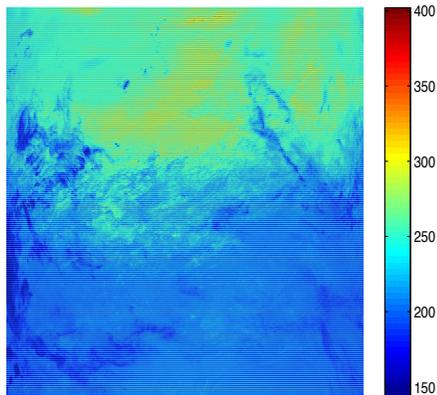
where $h_i(j)$ is the number of pixels sensor i measures digital count j , and N is the area of a sensor image in pixels. If there are L total scan lines with K pixels per scan, and M sensors then $N = K * L/M$. We will work directly with the cumulative histogram H , but the because the normalization by N is not important for destriping. However, the normalization is relevant to compression in that in the new space the dynamic range goes from 0 to N rather than to the max value of digital counts. As an example we consider the MODIS 1A EV_1km_night data. The imager has $M = 10$ sensors, $L = 2080$ scan lines and $K = 1400$ pixels per sensor and has a 12 bit range going from 0 to 4095. However, the imager only senses 2030 scan lines and 1354 pixels



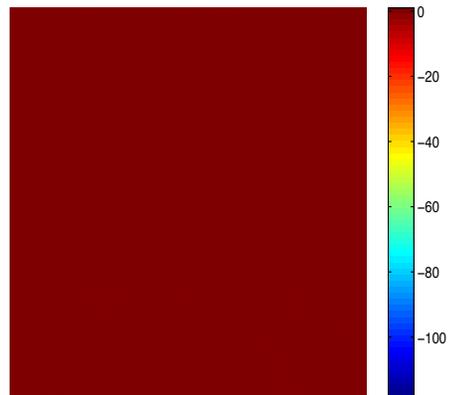
(a) Original Image



(b) Destriped Image

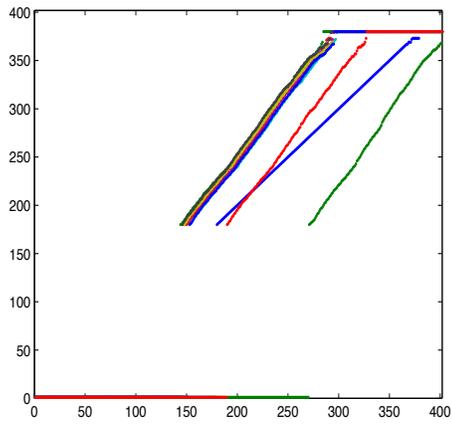


(c) Restriped Image

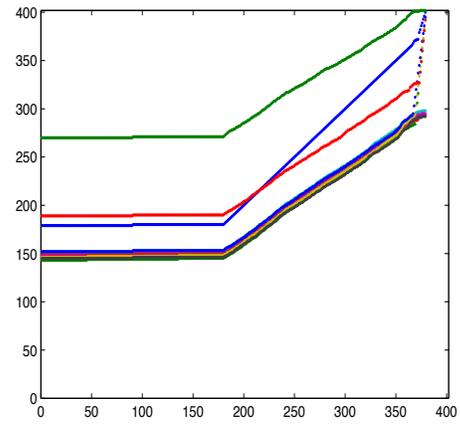


(d) Residual Image

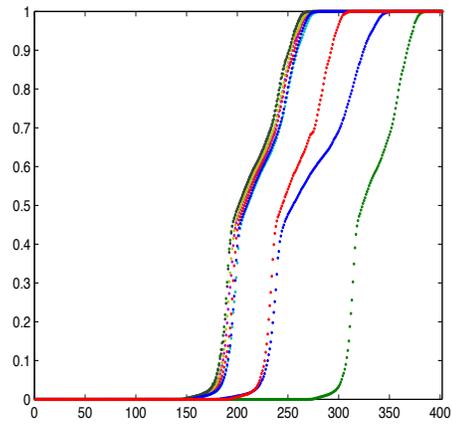
Figure 2. Destriping using specification: a) original image (channel 2 of EV_1km_night). b) destriped image using histogram specification. c) restriped image which is a result of applying the inverse look-up table of the original image to the destriped image. d) residuals of the original image and the restriped image.



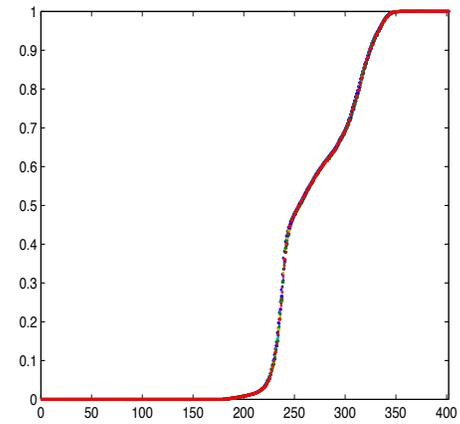
(a) Original Image



(b) Destriped Image



(c) Restriped Image



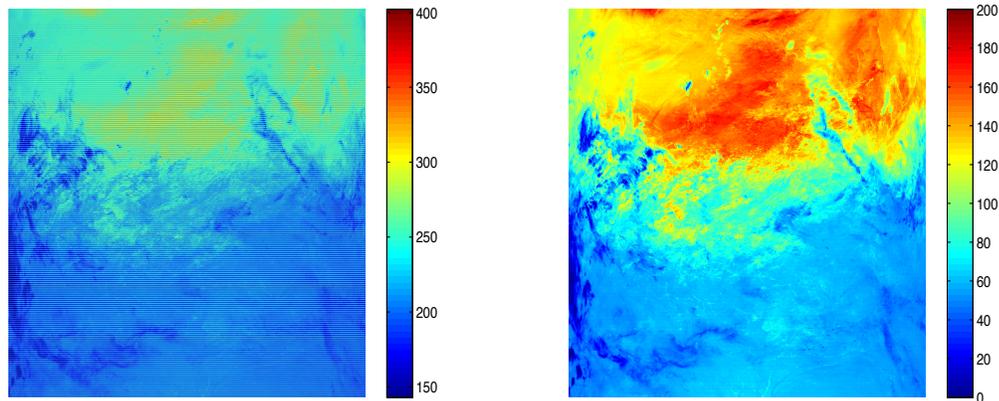
(d) Residual Image

Figure 3. a) Look-up table. b) Inverse look-up table. c) cumulative probability distribution of the original image per sensor. d) cumulative probability distribution of the destriped image per sensor.

per scan line. The remaining pixels are filled in with a value of -1. After the 10 sensors are equalized the cumulative histogram mapped range goes from 0 to $N = 274862$ just over 18 bits per pixel. This negatively impacts compression. The bit inflation is justified if the benefit in smoothing can offset the increase number of levels. It also should be noted that the equalization defined above results in a completely invertible (lossless) mapping of intensities.

2.2.1 Compressed equalization

The equalization certainly has the potential to inflate the number of bits per pixel that needs to be stored. In fact, the number of levels needed may be considerably less. In the case of modis of the MODIS 1A EV_1km_night data, after histogram equalization, each sensor can only produce 4096 distinct values within the 274863 possible equalized values. Even if each sensor's values did not overlap, this represents a worse case dynamic range of 0 to 40960 or just over 15 bits. Even if the sensors produce the values without overlap we can reduce the number of bits needed to represent the equalized image by conservatively allocating levels to the remapping. In particular histogram equalization satisfies two conditions: (1) it is 1-1 so that for each sensor the original (unequalized) level may be recovered losslessly and (2) it is monotonic across sensors so that if $P_{X_i}(\leq x_i) > P_{X_j}(\leq x_j)$ then $H_i(x_i) > H_j(x_j)$ with x_i and x_j coming from distinct sensors $i \neq j$. Although the histogram equalization satisfies



(a) Original image

(b) Destriped image with histogram equalization

Figure 4. Destriping using histogram equalization: a) Original image. b) Destriped image: notice that the range is different from that of the original image which is a result of compressed equalization.

these conditions there are other maps which also do but need not use as many levels. The algorithm to compress the lookup table works as follows. The goal of the algorithm is to produce k maps $m_i(x)$ for $1 \leq i \leq k$ from digital counts to a set of colors which is as small as possible and satisfies 2 conditions: (1) it should be 1-1 on each sensor and thus invertible (lossless) and (2) if $H_i(x_i) > H_j(x_j)$ then $m_i(x_i) \geq m_j(x_j)$. The algorithm to find the maps m_i starts by finding a sensor i and digital count that actually appears in the i th sensor image so that $H_i(x_i)$ is minimized. The first level $q = 0$ is allocated so that $m_i(x_i) = q$. In each subsequent step the next lowest value $H_j(x_j)$ is considered. If the current value of q has not yet been assigned to any element of m_j , then $m_j(x_j) = q$. If such an assignment has been made then q is incremented so $q = q + 1$ and then the assignment $m_j(x_j) = q$ is made. This minimizes the number of levels that need to be used to preserve the order with respect to the equalization, and preserve a 1-1 relationship for each map m_i .

We note that the lookup tables are not completely assigned. That is if a digital count x does not appear in the image there will not be a valid assignment $m_i(x)$ for that value. This is not a concern if the destriped image is compressed losslessly. If the destriped image is compressed with loss, then the other values of the table are assigned using linear interpolation. Figure 4 shows an image destriped using histogram equalization and Figure 5 is a pictorial representation of the compressed equalization process.

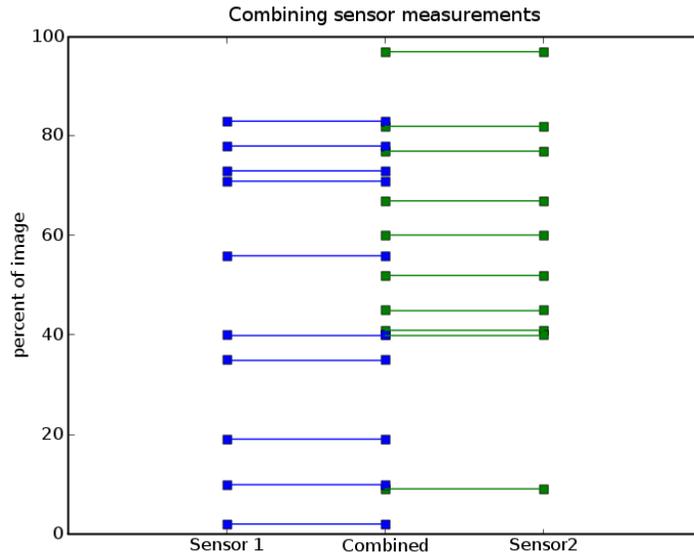


Figure 5. Compressed equalization

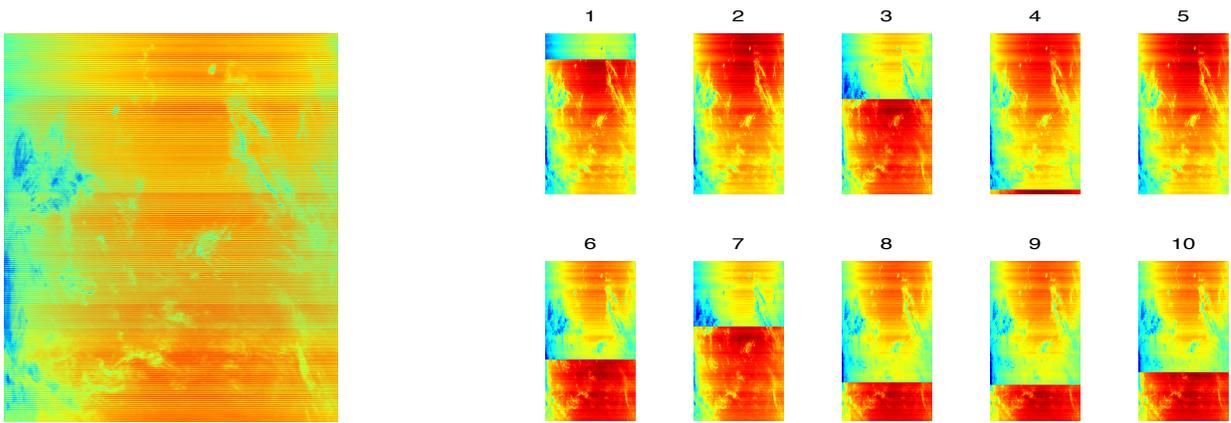
3. OFFSETS IN SENSOR IMAGES

Another eccentricity of the sensors is that there are offsets within a given sensor which we assume are a result of some “recalibration” process. Figure 6 shows an example of an image whose sensors have these offset eccentricities. Notice that different sensors have offsets at different scanlines. This problem could be remedied by adding corresponding constant factors to all of the subsequent scanlines of the sensor images that have offsets.

We determine additional constant factor by first computing the mean value of each scanline and if the image has an offset one would expect to find a jump in the array of mean values. We determine if its a jump by the following condition $|m_i - m_{i+1}| > 3 \cdot \text{std}\{|m_i - m_{i+1}|\}$, where m_i is the mean of the i 'th scanline. If this condition holds true we would like to think that there's a jump or offset and store the scanline index i and the value of the jump $m_i - m_{i+1}$.

4. LOSSLESS COMPRESSION OF DE-STRIPED SATELLITE IMAGES

Our lossless compression algorithm for images with significant stripes is outlined in this section. First we fix the offsets if there are any in the image using our technique in the previous section. Then we destripe the image using either of the techniques: histogram specification or histogram equalization. In the process of destriping we compute the look-up and inverse look-up tables where we store the inverse look-up table to get back to the original image. The destriped image is then compressed using one of the standard 2D compression algorithms available. The lossy image is then restored and restriped to get back the original image. In the case of destriping using histogram specification the lossiness is a result of both the destriping technique and the lossy 2D compression process while in the case of histogram equalization it is just a result of the 2D lossy compression of the destriped image as the destriping is an invertable process. After we restripe the lossy image using the inverse look-up table we then compute the residuals of the original image and the restriped image and entropy code these residuals. This algorithm is shown as a block diagram in Figure 7. The algorithm is applied to a few sample cases of the EV_1km_night images and the results or shown in Table 1.



(a) Example image with offsets

(b) Sensor images

Figure 6. Offsets: a) example of an image with offsets. b) corresponding sensor images of image a).

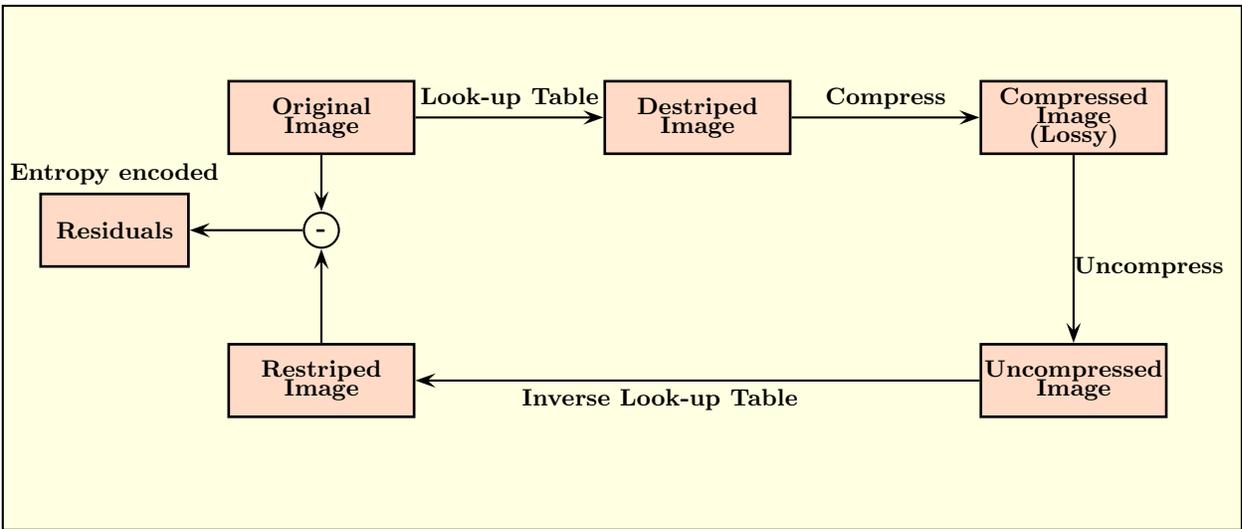


Figure 7. Compression algorithm block diagram

Table 1. Lossless compression ratios using de-striped images of different bands of EV_1km_night

Band	CR Original (JPEG2000)	CR de-striped	Percent Increase CR
2	3.48	4.23	18.00%
5	2.85	3.07	6.90%
6	1.95	2.04	4.16%
7	3.51	4.10	14.15%
8	3.15	3.66	13.90%
9	2.76	3.00	7.20%
11	2.36	2.62	9.76%
12	2.38	2.55	5.80%
13	2.32	2.44	4.70%
14	2.45	3.13	21.55%
15	2.53	2.62	4.45%

The compressed file consists of the inverse look-up table, the lossy compressed image and the entropy encoded residuals. Decompression of these files is a trivial process which involves the following steps: first we decompress the lossy image and restripe it using the inverse look-up table and decompress the entropy coded residuals. We then add the residuals to the restriped image to get back the original image.

5. CONCLUSION

We have observed significant gains in the lossless compression ratio between 4% to 22% just by taking spatial correlation into consideration. This shows that it is preferable to de-stripe the images prior to applying any compression technique to these images. Both the destriping techniques perform well with respect to compression algorithm, however the equalization method sometimes blows the bit-depth which worsens compression while specification method is not invertible and hence the residuals grow bigger which also affects compression. By taking both spatial and spectral correlations we have estimated the upper bound on the compression ratio and there seems to be a gap to be filled in with superior techniques designed solely for compression of hyper-spectral images. In this paper we have tested our claim on MODIS LWIR bands, in the future we would like to test on more satellite data as striping is a consistent anomaly albeit in the positive sense with respect to compression.

6. ACKNOWLEDGMENTS

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