ANOMALY-BASED HYPERSPECTRAL IMAGE COMPRESSION

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ABSTRACT

We propose a new lossy compression algorithm for hyperspectral images, which is based on spectral principal component analysis (PCA), followed by JPEG2000 (JP2K). The approach employs an anomaly-removal model in the compression process to preserve anomalous pixels. Results on two different hyperspectral image scenes show that the new algorithm not only provides good post-compression anomaly-detection performance but also improves rate-distortion performance.

1. INTRODUCTION

In hyperspectral image analysis, anomalies are important pixels since they are most likely man-made targets of interest. It is critical to preserve these pixels for target detection and discrimination in an unsupervised setting. However, these pixels are difficult to compress due to the fact that their spectral features are different from their surroundings.

In our previous study, it has been shown that principal component analysis (PCA) in conjunction with JPEG2000 (JP2K) can provide superior rate-distortion performance for hyperspectral image compression, where the PCA is applied for spectral decorrelation and JPEG2000 codes principal-component (PC) images. In particular, PCA+JP2K outperforms DWT+JP2K, the corresponding technique wherein a discrete wavelet transform (DWT) is adopted for the spectral transform. Thus, spectral decorrelation is key to hyperspectral compression, and PCA outperforms the DWT in this respect.

We also found that the best rate-distortion performance is provided when a subset of PCs is maintained for compression instead of all PCs [1], a strategy we refer to as SubPCA+JP2K. As for spectral fidelity, we employ the spectral angle mapper (SAM) and compute the average, peak, and standard deviation of spectral angles between the original and reconstructed pixels. In results in [2], although SubPCA+JP2K still provides the smallest average and standard deviation of spectral angles, the peak spectral angle is not the minimum mainly due to anomalous pixels. Since anomalous pixels tend to yield large reconstruction errors

spectrally, these pixels need special care in compression processes.

2. ANOMALY-ADJUSTED ALGORITHM

In [3], Penna *et al.* proposed a new compression algorithm that builds on PCA+JP2K by incorporating a model of anomalous pixels into the compression process. The model is based on the fact that there is always a considerable difference between the mean value over the whole hyperspectral image and the mean of the anomalous pixels alone. The compression algorithm essentially removes the mean difference from the anomalous pixels in the PCA domain and then restores the difference during the decompression process. This approach is referred to as the anomaly-adjusted (AA) algorithm in this paper.

The AA algorithm can provide improvement in post-compression anomaly detection with nearly unchanged rate-distortion performance, but there are several drawbacks. First of all, anomalies can be significantly different, so it does not necessarily work well to subtract the same mean difference from all anomalous pixels. Secondly, since the difference between anomalous pixels and their surroundings could be varied, the adjustment for a certain anomalous pixel can produce high-frequency components in the spatial DWT used in JP2K. Finally, since the eigenvectors used for PCA are calculated before the mean subtraction, some eigenvectors may not be accurate after mean subtraction depending upon the number of anomalies and how anomalous they are as compared to the surroundings.

3. PROPOSED ALGORITHM

To address the drawbacks discussed above, three major improvements are proposed as follows:

1. Each anomalous pixel is treated individually, and a 2D interpolation with neighboring pixels (rather than direct subtraction) is used to completely smooth out anomaly pixels while reducing the possible high-frequency components generated in the subsequent spatial DWT.
2. The original value and location coordinates of anomaly pixel vectors are stored in the compressed bitstream and used for decompression.
3. The manipulations of anomalies (i.e., interpolations) are all carried in the original image domain rather than in

the PCA domain, and PCA is conducted after all the anomalies are removed, which guarantees that anomalies do not affect PCA.

Anomalous pixels will be compressed separately in a lossless manner, while the rest image will be compressed using PCA+JP2K or SubPCA+JP2K. In this case, the covariance matrix used in PCA does not include any information from these anomalous pixels. As a result, the background can be efficiently compressed while leaving the anomalies intact. Due to the fact that we essentially remove the anomalies from the original image during its compression, we name our approach anomaly removal (AR). Note that, in practice, we may not compress the anomalous pixels at all for system simplification, which may not entail significant impact on rate-distortion performance because of the small number of these anomalous pixels.

Figure 1. Encoder of the proposed AR algorithm.

As illustrated in Fig. 1, the encoder of the proposed AR-based algorithm has the following steps.

1. Apply an anomaly-detection algorithm (e.g., the RX algorithm [4] in this study) on the original image to detect anomalies. Let these pixels belong to the set A , i.e., $\{y_i | i \in A\}$.
2. For each anomalous pixel, a 2D interpolation, which replaces the value of an anomalous pixel with the mean value of its eight surrounding pixels, is performed individually.
3. The value and location coordinates of the anomalies are saved in the bitstream for the decoder.
4. PCA is processed on the anomaly-removed image to generate a transform matrix.

5. For the SubPCA+JP2K case, the optimal number of PCs is found and a transform matrix is determined.
6. Send the spectral transform matrix and mean vectors to JP2K encoder, which will conduct the spectral transform, spatial coding of PC images, and automatic bit allocation; the bitstream is generated with transform matrix, mean vector, and anomaly information embedded.

Figure 2. Decoder of the proposed AR algorithm.

As for the decoder of the AR-based algorithm, it simply performs similar steps as in the reverse order of the encoding part. The block diagram is shown in Fig. 2 with the detailed description being as follows.

1. JP2K decoding of each PC is first performed.
2. Inverse PCA is performed.
3. The coordinated and values of anomalous pixels in A are read from the compressed file.
4. The actual anomalous pixels are put back to the corresponding locations in the reconstructed image.

4. PERFORMANCE EVALUATION

The performance metrics used in our experiments are signal-to-noise ratio (SNR) for rate-distortion performance, and receiver operating characteristics (ROC) for anomaly-detection performance.

Let (i, j, k) denote a data coordinate in an $L \times M \times N$ hyperspectral image with a variance of σ^2 , where L is the number of bands, M and N are the number of rows and columns in each band, respectively. Let $\tilde{r}(i, j, k)$ denote the reconstructed data point from decompression of $r(i, j, k)$. The mean-squared-error (MSE) is defined as

$$MSE = \frac{1}{LMN} \sum_{i,j,k} [r(i, j, k) - \tilde{r}(i, j, k)]^2 \quad (1)$$

and SNR in decibels (dB) is defined in terms of the MSE as

$$SNR = 10 \log_{10} \frac{\sigma^2}{MSE}. \quad (2)$$

The detailed procedure of generating an ROC curve from a reconstructed image is listed as follows

1. Perform the RX-based anomaly detection to generate an anomaly-detection map from the reconstructed image.
2. Rescale pixel values in the anomaly map to [0,1].
3. Convert the anomaly map into a binary image by hard thresholding it with the threshold being gradually changed from 1 to 0; if a pixel has the value of 1, this pixel is claimed as an anomaly.
4. Let d denote the number of extracted anomalies that is a part of the ground-truth anomalies, let f denote the number of extracted anomalies that is not a part of the ground-truth anomalies, and let s denote the total number of extracted anomalies in an anomaly-detection map. For each threshold, count d , f , and s . Then, the detection probability P_d and false-alarm probability P_{fa} can be calculated by

$$P_d = \frac{d}{n}, P_{fa} = \frac{f}{s-n}. \quad (3)$$

where n is the number of actual anomalies to be detected.

5. An ROC curve can be drawn with all the thresholds being finished in Steps 3 and 4.

5. EXPERIMENTAL RESULTS

Two real hyperspectral images were used in the experiments. The first one is the Moffett scene taken by Airborne Visible/InfraRed Imaging Spectrometer (AVIRIS), which has 224 bands and 512×512 pixels with 20-m spatial resolution. The second image was taken by the Compact Airborne Spectrographic Imager (CASI), which has 72 bands and 150×250 pixels with 2-m spatial resolution. In addition to the original PCA+JP2K and SubPCA+JP2K, there were two AA versions (AA+PCA+JP2K and AA+SubPCA+JP2K) and two AR versions (AR+PCA+JP2K and AR+SubPCA+JP2K) implemented for comparison.

5.1. Rate-distortion results

The rate-distortion performance for the Moffett data is sketched in Fig. 3, and detailed SNR values are tabulated in Table 1. We can see that all the SubPCA-based algorithms outperformed the corresponding PCA-based algorithms; all the SubPCA-based algorithms performed similarly in terms of rate-distortion performance; and all the PCA-based algorithms performed similarly. As listed in Table 1, the SNR values from the AA-based algorithms were slightly lower than the originals, and the SNR values from the AR-based algorithms were slightly greater. Overall, however, AA and AR approaches did not significantly affect the rate-distortion performance.

The rate-distortion performance for the CASI data is shown in Fig. 4 and Table 2. The AR algorithms showed significant SNR gain (e.g., 5 dB at 1.0 bpppb). AR+SubPCA+JP2K provided the best rate-distortion performance, followed by AR+PCA+JP2K, while AA+SubPCA+JP2K performed similarly to SubPCA+JP2K, which were in turn better than AA+PCA+JP2K and PCA+JP2K. As shown in Table 2, the SNR values from the AA versions were slightly lower than the original algorithms; however, SNR values from the AR versions were greater, particularly at high bitrates.

Figure 3. SNR curves for Moffett data.

Table 1. SNR results for Moffett data.

Moffett	0.2 bpppb	0.5 bpppb	1.0 bpppb
PCA+JP2K	42.268 dB	47.017 dB	50.919 dB
SubPCA+JP2K	42.927 dB	47.168 dB	50.993 dB
AA+PCA+JP2K	42.230 dB	46.977 dB	50.816 dB
AA+SubPCA+JP2K	42.895 dB	47.131 dB	50.905 dB
AR+PCA+JP2K	42.284 dB	47.044 dB	50.943 dB
AR+SubPCA+JP2K	42.948 dB	47.197 dB	51.017 dB

Figure 4. SNR curves for CASI data.

Table 2. SNR results for CASI data.

CASI	0.2 bpppb	0.5 bpppb	1.0 bpppb
PCA+JP2K	21.557 dB	27.618 dB	30.020 dB
SubPCA+JP2K	22.792 dB	27.839 dB	30.054 dB
AA+PCA+JP2K	21.517 dB	27.607 dB	30.019 dB
AA+SubPCA+JP2K	22.762 dB	27.831 dB	30.051 dB
AR+PCA+JP2K	22.498 dB	30.142 dB	35.204 dB
AR+SubPCA+JP2K	23.935 dB	30.571 dB	35.341 dB

The performance discrepancy in the Moffett data and CASI data is due to the fact that anomalies in CASI data are more different from each other and more distinctive from the background. Thus, completely removing them makes the compression of the rest image more efficient.

4.2. Anomaly detection results

The ROC curves for the Moffett data at 1.0 bpppb are sketched in Fig. 5. As we can see, the AR-based algorithms (both for PCA and SubPCA) significantly outperformed all the other algorithms. Meanwhile, the AA-based algorithms also provided better results than the original ones. However, AA+PCA+JP2K could not compete with SubPCA+JP2K without anomaly adjustment or removal.

The ROC curves for the CASI data at 1.0 bpppb are sketched in Fig. 6. The AR-based algorithms (both for PCA and SubPCA) still performed the best. In this case the AA versions did not bring about improvement compared to the originals (AA+PCA+JP2K did similarly to PCA+JP2K, and AA+SubPCA+JP2K did similarly to SubPCA+JP2K). In addition, AA+SubPCA+JP2K and SubPCA+JP2K could not compete with AA+PCA+JP2K and PCA+JP2K.

Thus, the AR-based algorithms are more powerful in anomaly detection since all the anomalies are well preserved without compression (or with lossless compression). Using the AR approach is more critical for SubPCA+JP2K, since SubPCA+JP2K keeps only major PCs. In the cases that the PCs participating in the subsequent compression do not contain anomaly information (such as the case of CASI data), this information will be sacrificed.

5. CONCLUSIONS

We proposed a new approach to preserve anomaly information by extracting these pixels before compression and transmitting them losslessly. We saw that this approach can improve not only the post-compression anomaly-detection performance but also the rate distortion performance. Its advantage is more significant when anomalies are strong and significantly different. It is particularly helpful to SubPCA+JP2K in preserving anomaly information that is usually present in minor PCs.

Figure 5. ROC curves for Moffett data at 1.0 bpppb.

Figure 6. ROC curves for CASI data at 1.0 bpppb.

6. REFERENCES

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