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Lossless and near-lossless compression of hyperspectral images based on distributed source coding

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ABSTRACT

This paper addresses the problem of the lossless and near-lossless compression of hyperspectral images and presents two efficient algorithms based on distributed source coding, which perform the lossless compression by means of multilevel scalar codes. The proposed algorithms are implemented on the co-located blocks in the spectral orientation. A novel multiband spectral predictor is proposed to construct the side information of each block. The back-up side information is introduced for the second algorithm to recover the images when the original side information is corrupted by errors. The encoder only requires the transmission of the least significant bit (LSB) bit-planes to the decoder, and the number of bits is computed by the maximum error between the block and its side information. The proposed algorithms are also extended to near-lossless compression. The experimental results show that the proposed algorithms have a competitive compression performance with the existing distributed compression algorithms. Moreover, the proposed algorithms can provide low complexity and different degrees of error resilience, which is suitable for onboard compression.

1. Introduction

Hyperspectral imaging is an important technique in the field of remote sensing that is characterized by high resolutions in the spectral dimension. With the increase of spectral and spatial resolutions, the availability and dimensionality of hyperspectral images is continuously increasing. This demands an efficient compression technique that can be used to compress the hyperspectral images and to reduce the data size as much as possible. Image compression techniques can be employed to solve this problem, allowing the transmission of more data in the same amount of time. Several types of compression methods are available. In lossless compression, the reconstructed image is identical to the original. In near-lossless compression, the maximum absolute difference between the reconstructed image and the original image does not exceed a defined peak value. For lossy compression given a target bit-rate, the reconstructed image is as similar as possible to the original image in the mean-squared error sense. Lossy compression may provide a high compression degree. However, the incurred distortion can greatly affect the performance of the practical application for hyperspectral images. Although the compression degree of lossless compression is limited, it can preserve all of the information perfectly. Near-lossless compression reduces the bit-rate by introducing a limited peak error to preserve the quality of images. At present, lossless and near-lossless compression have received more attention for the onboard compression of hyperspectral images.

In general, the satellite or spacecraft-based platforms have limited capacity for storage memory and computational resources. As a result, these systems usually employ a simple technique to perform hyperspectral images compression [1]. While compression is becoming more and more important for onboard processing, it should be noted that the pursuit of high compression performance should not be the only purpose. Because the onboard dataset requires transmission to the ground, the compression algorithms should be error resilient because of the bad channel environment. In practice, near-lossless compression is typically implemented by employing a quantizer followed by lossless compression. As a matter of fact, the prediction-based lossless compression can be extended to near-lossless compression combined with a quantation operation. The existing lossless compression algorithms are generally designed using linear prediction, transform or vector quantization, where the prediction-based technique is widely used to perform the lossless and near-lossless compression, while the transform-based technique is mainly used for lossy compression.

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Because of the high complexity, the vector quantation-based technique is scarcely used. As we know, both the JPEG-LS [2] and the context-based adaptive lossless image coding (CALIC [3]) algorithms are well-known compression standards that perform two-dimensional lossless compression. Note that the CALIC algorithm has also been extended to the three-dimensional CALIC (3D CALIC) algorithm to perform the lossless compression of multispectral images [4], where the extension consists of a fairly simple spectral predictor that uses one previous band to predict the current band. In [5], Magli E used the 3D CALIC algorithm to perform near-lossless compression on hyperspectral images. Moreover, Magli E proposed an optimized onboard near-lossless compression of the hyperspectral data using the CALIC algorithm referred to as M-CALIC, which has been proposed for onboard compression. The M-CALIC algorithm uses a more efficient spectral predictor than that of the 3D CALIC algorithm followed by the CALIC algorithm for spatial compression. Rizzo F proposed a low complexity algorithm for hyperspectral image compression that uses linear prediction in the spectral domain, which is suitable for onboard implementation because of the limited hardware and low power consumption [6]. Rizzo F also proposed a spectral-oriented least square (SLSQ) algorithm that uses two prediction modes: intra-band prediction and inter-band prediction for hyperspectral images, which achieves a competitive performance at a lower complexity [6]. Note that an excellent lossless compression performance is achieved by using the class-based inter-band prediction, which is reported in [7,8]. Although these algorithms provide a satisfying compression performance, they still have a significantly high complexity and no error resilience in terms of the constraint of onboard compression, even if these algorithms are extended to near-lossless compression. In recent years, a new method to encode statistically dependent sources called distributed source coding (DSC) has received more and more attention because it can provide both low complexity and error resilience, thus satisfying the requirement of onboard compression systems [9–11]. DSC was originally designed for lossless compression using the basis of the Slepian–Wolf theory [12]. Magli E proposed a scalar-DSC (s-DSC) using multilevel coset codes [13]. Based on s-DSC, Andrea A proposed three DSC-based lossless compression algorithms that provide both low complexity and error resilience [14]. Compared with the traditional compression algorithm, the performance of the existing DSC-based compression is not satisfying because it is less sufficient than the correlation model when it is subjected to the complexity constraints. However, the resulting DSC-based compression algorithms have been proposed for lossless compression, whereas they have not yet been tested in the near-lossless case. In this paper, we proposed efficient DSC-based lossless and near-lossless compression algorithms for hyperspectral images by using multilevel scalar codes, which have a competitive compression performance compared with the existing DSC-based algorithms. Furthermore, the proposed algorithms provide both low complexity and different degrees of error resilience, which is suitable for the onboard compression of hyperspectral images.

This paper is organized as follows. In Section 2, we describe the first proposed DSC-based algorithm for the lossless compression of hyperspectral images. In Section 3, we describe the second proposed DSC-based algorithm. In Section 4, the proposed algorithms are extended to near-lossless compression. The performance evaluation of the proposed algorithms is reported in Section 5. Finally, conclusions are drawn in Section 6.

2. M-DSC1 algorithm

In the DSC scenario, two (or more) statistically dependent data sources must be encoded by separate encoders that are not allowed to talk to each other. Lossless compression is performed on each source separately and may be less efficient than the joint encoding of all sources. However, the DSC theory proves that under certain assumptions, the effect of separate encoding is equivalent to that of joint encoding, while the sources are decoded jointly [12]. In practice, the DSC theory can be typically carried out by using binary error-correcting codes or multilevel scalar codes [15–17]. Binary error-correcting codes mainly include Turbo, LDPC, Trellis or other powerful binary channel codes, while multilevel scalar codes are mainly the (n, k) linear grouping codes. It should be noted that the performance of the binary error-correcting codes is worse than that of the multilevel scalar codes because they neglect the correlations between the bit-planes. Therefore, the proposed algorithms employ the (n, k) linear grouping codes to perform distributed lossless compression. Suppose the original source is represented by n bits. Then, the (n, k) linear grouping codes partition the set of 2^n values into 2^r cosets with 2^k elements in each coset, where $r = n - k$. The Euclidian distance between the adjacent two elements in every coset is 2^r. Note that each pixel must belong to one of the cosets, and the two arbitrary cosets have no common element. When compared with the traditional algorithm, the DSC encoder only needs to transmit the label of the coset to which each pixel belongs instead of the prediction errors to the decoder. At the decoder, the pixel is reconstructed in the coset, is indexed by the received coset label and is combined with its side information.

2.1. Construction of the side information

For the DSC encoder, the quality of the side information can significantly influence the compression performance. It is expected that the side information should be as close as possible to the pixel being encoded, which allows the use of the smallest number of bits for the coset label while achieving perfect reconstruction. In general, we can directly select the previously adjacent band as the side information of the current band. However, it is not an effective band for the hyperspectral images. As we known, the spectral correlation of the hyperspectral images is fairly high so that the current band is typically correlated with a few previous bands. This correlation should be better explored to achieve a high compression performance. To take advantage of the local characteristics of the hyperspectral images, each band is partitioned into non-overlapping blocks of size $N \times N$. Let $x_{k,i,j}$ denote the pixel of the current block in the i-th line, j-th pixel, and k-th band with $k = 1, 2, \ldots, L$ and $i, j = 1, 2, \ldots, N$. The side information of the current pixel $x_{k,i,j}$ is constructed linearly from the decoded pixels of the co-located blocks in the previous P bands. The side information of the current block can be expressed as

$$\bar{x}_{k,i,j} = \sum_{l=1}^{P} \alpha_l (x_{k-l,i,j} - \mu_{k-l}) + \mu_k, \quad i,j = 1,2,\ldots,N \tag{1}$$

where μ_k is the average value of the block in the k-th band and $\boldsymbol{\alpha}_k = [\alpha_1, \alpha_2, \ldots, \alpha_P]$ are the prediction coefficients. Note that the prediction coefficients are computed by minimizing the energy of the prediction errors of the current block, which can be written as

$$(\boldsymbol{G}\boldsymbol{\alpha}_k - \boldsymbol{H})^T (\boldsymbol{G}\boldsymbol{\alpha}_k - \boldsymbol{H}) \tag{2}$$

where

$$\boldsymbol{G} = \begin{bmatrix} x_{k-1,1,1} - \mu_{k-1} & x_{k-p,1,1} - \mu_{k-p} \\ \vdots & \vdots \\ x_{k-1,N,N} - \mu_{k-1} & x_{k-p,N,N} - \mu_{k-p} \end{bmatrix} \quad \boldsymbol{H} = \begin{bmatrix} x_{k,1,1} - \mu_k \\ \vdots \\ x_{k,N,N} - \mu_k \end{bmatrix} \tag{3}$$

The optimal prediction coefficients are calculated over the block by the least-square estimator as follows