Distributed compression for hyperspectral images

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Abstract: An efficient lossy compression algorithm was presented based on distributed source coding. The proposed algorithm employed multilevel coset codes to perform distributed source coding and a block-based scalar quantizer to perform lossy compression. Multi-bands prediction was used to construct the side information of each block, and the scalar quantization was performed on each block and its side information simultaneously. According to the principles of distributed source coding, the bit-rate of each block after scalar quantization was given. To reduce the distortion introduced by scalar quantization, skip strategy was employed for those blocks that containing high distortion in the sense of mean squared errors introduced by scalar quantization, and the block was directly replaced by its side information. Experimental results show that the performance of the proposed algorithm is competitive with that of transform-based algorithms. Moreover, the proposed algorithm has low complexity which is suitable for onboard compression of hyperspectral images.

Key words: hyperspectral images; lossy compression; distributed source coding; scalar quantization

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超光谱图像的分布式压缩

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摘 要: 针对超光谱图像压缩进行了研究，提出了一种有效的基于分布式信源编码(Distributed Source Coding, DSC)的有损压缩算法。该算法利用多元陪集码和标量量化的方式实现超光谱图像的分布式有损压缩,针对分布式信源编码,利用多波段预测的方式为每个编码块构造边信息,然后采用标量量化的方式对编码块和其边信息同时进行量化处理。根据分布式信源编码原理，给出了各编码块量化后的编码码率。为了减少标量量化带来的信息丢失,算法引入了跳跃策越。部分均方误差意义上损失较大的编码块将由其边信息直接代替。实验结果表明,所提出的算法性能与基于小波变换的算法性能相当;此外,该算法复杂度较低,适合星载超光谱图像的压缩。

关键词: 超光谱图像； 有损压缩； 分布式信源编码； 标量量化

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0 Introduction

Hyperspectral remote sensing has been paid more attention in the recent years. Since hyperspectral imaging technique provides more accurate and detailed information extraction than possible with any other type of remotely sensed data, it has been widely used in a large number of applications. The hyperspectral images are usually acquired by a remote platform (a satellite or an aircraft), and then downlinked to a ground station. With the increase of the image resolution, the data volume increase rapidly, which creates the great challenges for onboard storage and transmission. Due to the huge size of the datasets, lossy compression manner should be taken into account for hyperspectral images compression.

As we know, besides the spatial correlation, hyperspectral images also have strong correlation in the spectral direction. Regarding the transform used to decorrelate the spectral correlation, two approaches must be taken into account[1-5]: the DWT (Discrete Wavelet Transform) and the KLT (Karhunen–Loève Transform). Note that both DWT and KLT have been included in part two of the JPEG2000 standard, which are defined for both lossless and lossy compression[6]. However, transform-based algorithms are not suitable for the on-board compression due to the high encoder complexity and poor error resilience. DSC (Distributed source coding) has been paid more and more attention[7]. Different from the source coding methods, DSC is typically performed by powerful channel codes, such as multilevel coset codes or binary error-correcting codes, where multilevel coset codes mainly contain (n, k) linear grouping codes while binary error-correcting codes mainly contain Turbo, LDPC (Low Density Parity Check) and so on[8]. DSC was originally used for lossless compression with its basis of Slepian-Wolf theory[9]. Wyner A D and Ziv J later proposed the corresponding theory for DSC lossy compression based on the Slepian-Wolf theory[10]. Nonnis A proposed a DSC-based lossless compression, which employs Slepian-Wolf coding of the bit-planes of the CALIC prediction errors to improve the compression performance[11]. However, the common shortage of the above algorithms is that the correlation estimation is supposed to be known beforehand. Although distributed source coding schemes are typically based on the use of channels codes as source codes, Grangetto M proposed a new paradigm named distributed arithmetic coding, which extends arithmetic codes to the distributed case employing sequential decoding aided by the side information[12]. Magli E proposed two DSC–based lossless compression algorithms by using multilevel coset codes[8]. Andrea A developed three distributed lossless compression algorithms, which provide different tradeoffs between compression performance, error resilience, and complexity[13]. Nian Y J extended the distributed lossless compression to near lossless compression[14] and lossy compression[15]. According to the above description, we can see that the DSC–based compression by using multilevel coset codes is mainly focus on lossless compression. In this paper, we extended the DSC–based lossless compression to lossy compression and proposed an efficient lossy compression algorithm based on distributed source coding. Experimental results show that the proposed algorithm can provide competitive performance and low complexity compared with the transform-based algorithms.

This paper is organized as follows. In Section 2, we describe the DSC–based compression briefly and describe the proposed distributed lossy compression of hyperspectral images based on scalar quantization. The compression performance evaluation of the proposed algorithm is reported in Section 3. Finally, conclusions are drawn in Section 4.

1 Distributed lossy compression based on scalar quantization

1.1 Side information

First, each band is partitioned into nonoverlapping square blocks with a size of $N\times N$. Let $x_{k,i,j}$ be the pixel of the current block in the i-th line, j-th pixel, and k-th band, with $k=1,2,\cdots,L$ and i, $j=1,2,\cdots,N$. To design a compression algorithm with low encoder complexity, it has been decided to employ a reference band based on a linear combination of the previous two bands [15-16]. Let m_k be the average value of the current block, the side information is generated as follows

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

where $\alpha_k=[\alpha_1,\alpha_2]^T$ are the prediction coefficients. The goal of the side information is as close as possible to the current block with respect to the standard of minimum mean-squared error. The principle of the prediction coefficients is to minimize the energy of the prediction errors which can be written as

$$(P\alpha_k-Q)^T(P\alpha_k-Q) \tag{2}$$

where

$$P=\begin{bmatrix} x_{k-1,1,1}-\mu_{k-1} & x_{k-2,1,1}-\mu_{k-2} \\ \vdots & \vdots \\ x_{k-1,N,N}-\mu_{k-1} & x_{k-2,N,N}-\mu_{k-2}\end{bmatrix},\ Q=\begin{bmatrix} x_{k,1,1}-\mu_k \\ \vdots \\ x_{k,N,N}-\mu_k\end{bmatrix} \tag{3}$$

By using the least-square estimator, the optimal α_k can be expressed as follows

$$\alpha_1=\frac{C_{k,k-2}C_{k-1,k-2}-C_{k,k-1}C_{k-2,k-2}}{C_{k-1,k-2}^2-C_{k-1,k-1}C_{k-2,k-2}} \tag{4}$$

$$\alpha_2=\frac{C_{k,k-1}C_{k-1,k-2}-C_{k,k-2}C_{k-1,k-1}}{C_{k-1,k-2}^2-C_{k-1,k-1}C_{k-2,k-2}} \tag{5}$$

where $C_{k-u,k-v}$ is the correlation coefficient between the co-located blocks in the u-th band and v-th band, which is expressed as follows

$$C_{k-u,k-v}=\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}(x_{k-u,i,j}-\mu_{k-u})(x_{k-v,i,j}-\mu_{k-v}) \tag{6}$$

The errors between the current block and the side information are computed as follows

$$e_{k,i,j}=x_{k,i,j}-\bar{x}_{k,i,j} \quad i,j=1,2,\cdots,N \tag{7}$$

1.2 Quantization strategy

In particular, the scalar quantization manner has been widely used in the prediction-based lossy compression algorithm for hyperspectral images due to the simple implementation. Let q_k be the quantization step size of the current block in the k-th band, thus the quantized version of the current block is given as

$$y_{k,i,j}=\frac{x_{k,i,j}}{q_k} \tag{8}$$

Under the condition of lossy compression, the side information of the current block is constructed as follows

$$\bar{x}_{k,i,j}=\sum_{l=1}^{2}a_l(\hat{x}_{k-l,i,j}-\hat{m}_{k-l})+m_k \tag{9}$$

where $\hat{x}_{k-l,i,j}$ is the reconstructed value of the co-located block in the $(k-l)$-th band and m_{k-l} is the average value. The quantized version of the side information is also given as

$$\bar{y}_{k,i,j}=\frac{\bar{x}_{k,i,j}}{q_k} \tag{10}$$

The error between the current block and its side information is given as

$$e_{k,i,j}=\text{round}(y_{k,i,j})-\bar{y}_{k,i,j} \tag{11}$$

In fact, the bit-rate of the current block is just the LSBs that required to be transmitted to the decoder. According to the expression of bit-rate without any quantization proposed in[13], we can simply obtain the bit-rate of the quantized version of the current block as follows

$$R_k=\left\lceil \log_2\left(\frac{\max\limits_{i,j=1,2,\cdots,N}|e'_{k,i,j}|}{q_k}\right)\right\rceil \tag{12}$$

Once obtain the bit-rates of co-located blocks in the spectral orientation, the total bit-rate of these blocks is computed as

$$R_f=\frac{1}{L}\sum_{k=1}^{L}R_k \tag{13}$$

The distortion between the original block and the reconstructed one is given as

$$e_{k,i,j}=x_{k,i,j}-\hat{x}_{k,i,j} \tag{14}$$

where

$$\hat{x}_{k,i,j}=\text{round}(y_{k,i,j})*q_k \tag{15}$$

1.3 Skip strategy

When the target bit-rate is low, for a given block, the introduced distortion by scalar quantization may be too large. In this case, to reduce the introduced distortion, the "skip" strategy is employed for the proposed algorithm. Note that skip scheme has been used in video coding and hyperspectral images coding[16-17]. In this situation, we can neglect the LSBs that need to be transmitted by using a flag that indicated to the decoder to simply replace the block with its prediction values. If the current block determined to be skipped, the reconstructed values of the current block are given as follows

$$\hat{x}_{k,i,j}=\text{round}(\bar{x}_{k,i,j}) \tag{16}$$

The distortion between the original block and the reconstructed block is given as

$$e_{k,i,j}=x_{k,i,j}-\hat{x}_{k,i,j} \tag{17}$$

In practice, we use the MSE (Mean Squared Errors) to measure the distortion of each block, which is given as

$$D=\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}e_{k,i,j}^2 \tag{18}$$

For a given block, if the D value obtained by the scalar quantization is less than that obtained by the skip strategy, this block will be processed by scalar quantization, otherwise, it will be skipped and replaced by its side information. Based on the above description, the proposed algorithm can be shown in Fig.1.

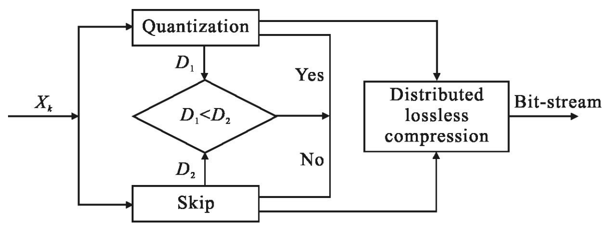


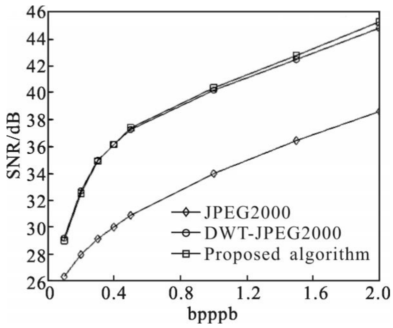
Fig.1 Flowchart of the proposed algorithm

2 Experimental results and discussion

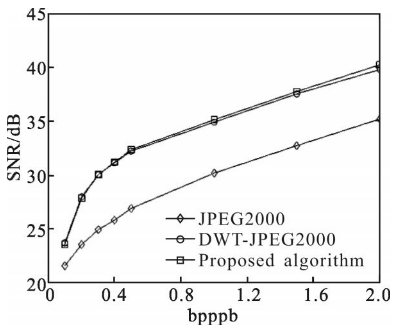
The performance of the proposed scheme was tested on Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) hyperspectral images. AVIRIS is an airborne hyperspectral system that collects spectral radiance in 224 contiguous spectral bands with wavelengths from 400 to 2 500 nm. In particular, two scenes from the 1997 missions are used for evaluation of compression algorithms.

2.1 Compression performance

We use bpppb (bit per pixel per band) and SNR (Signal to Noise Ratio) to evaluate the compression performance. As we know, the transform-based algorithm can provide perfect rate-distortion performance for lossy compression. In this paper, the proposed algorithm is compared with JPEG2000 and DWT-JPEG2000 with a large range of bit-rates. The compression results on AVIRIS images by various algorithms are shown in Fig.2. As can be seen, the compression performance of JPEG2000 is the worst because it does not remove the spectral correlation of hyperspectral images, the proposed algorithm and DWT-JPEG2000 both significantly improve the compression performance compared with JPEG2000. As for the proposed algorithm, the performance is obviously slightly better than that of DWT-JPEG2000 at high bit-rates and slightly worse at low bit-rates; this is because the multi-prediction has the disadvantage of error accumulation at low bit-rates, which can seriously degrade the compression performance while this disadvantage does not exist at the high bit-rates. On the other hand, compared with DWT-JPEG2000, a large number of blocks will be directly skipped at low bit-rates, which is the other reason of the performance decrease for the proposed algorithm. However, this disadvantage can be completely negligible at high bit-rates. For the reason of fact that high bit-rates compression is usually used for onboard compression in order to preserve the information of hyperspectral images as much as possible. Therefore, the proposed algorithm is a better choice when the bit-rate is not very low. In fact, the prediction-based algorithm is not suitable for lossy compression and transform-based algorithm is suitable for lossy compression. As for the proposed algorithm, the proposed algorithm has competitive rate-distortion performance with DWT-JPEG2000, which fully shows the affection of the proposed algorithm. It should be noted that when the quantization step equals to one, the proposed algorithm becomes the distributed lossless compression. Therefore, the proposed algorithm can realize both lossless and lossy compression for hyperspectral images.



(a) Cuprite



(b) Lunar Lake

Fig.2 Compression performance for the AVIRIS images

2.2 Complexity

For the block size (N=32), computing the mean value within a block and subtracting it from the pixels requires about 2 additions per pixel. Computing prediction coefficients requires 5 additions and 5 multiplications per pixel. Computing the side information requires 1 addition and 2 multiplications per pixel, and computing the errors requires 1 addition per pixel. Computing the bit-rate can be done by using table lookup. Computing the quantized version and the reconstructed one of the current block requires 2 multiplications per pixel. Computing the MSE of the scalar quantization requires 2 additions and 1 multiplication per pixel while the MSE of the skip strategy requires 1 addition and 1 multiplication per pixel. Computing the map and the coset label only requires bitwise operations. For differential Rice coding, the computation of index differences between entries at one in the binary mask requires at most 1 operation per pixel. Thus, on average, for the encoding process, it requires to perform approximately 17 additions and 11 multiplications on each pixel for the proposed algorithm. As for DWT-JPEG2000, the complexity of spectral transform and the encoding procedure is obviously much higher than that of the proposed algorithm.

3 Conclusion

Transform-based lossy compression algorithms have been widely used for hyperspectral images compression. However, these algorithms have shortages of high complexity and poor error resilience, which cannot satisfy the requirements of onboard compression. We have proposed an effective compression algorithm for hyperspectral images based on distributed source coding, which employs scalar quantization and skip strategy to perform lossy compression. Its rate-distortion performance is typically equal or better than the transform-based algorithm, with significantly lower complexity and memory requirements. As the high sensor-data rates of present and future hyperspectral missions call for simple and fast compression techniques, the proposed algorithms represent an attractive choice for onboard compression, with the compensated by the error resilience.

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