Optimal Recursive Bidirection Prediction for Hyperspectral Image Compression

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Abstract. In this paper, we propose a new algorithm named Optimal Recursive Bidirection Prediction (ORBP) for HyperSpectral Image (HSI) compression. Recursive Bidirection Prediction (RBP) is a good algorithm for HSI inter-band prediction. It’s simple, efficient. But the algorithm can’t get optimal prediction result under the sense of SNR. In this paper, the linear model of HSI is established, and the best prediction is deduced under the sense of SNR. The proposed method can get lower entropy after prediction. Computer simulation results show that compared with the traditional algorithm RBP, the proposed method ORBP has a great improvement by about 9.2738dB in SNR in average.

1. Introduction
Hyperspectral imaging spectrometer can get images in many narrow, contiguous, spectral bands. So HSI offers a more detailed view of the spectral properties of a scene. The typical sensor for HSIs is Airborne Visible/InfRared Imaging Spectrometer (AVIRIS). It simultaneously collects spectral information in the visible to infrared ranges and records it in 224 continuous spectral bands that range from 0.4 to 2.4mm. Each of them has an approximately 10nm. HSI has high spectral resolution, which is important to classification and detection [1-2].

Compared with multispectral image, HSI has two specific characteristics. First, a huge volume of image data accompanies the increase of the high spectral resolution. For example, a standard AVIRIS image occupies a data cube of 512 lines by 614 columns by 224 bands and takes about 140Mbytes. HSI has huge data volume and high data dimensionality, which brings a lot of difficulties to storage and transmission. So it is desirable to develop efficient compression algorithm. Another characteristic is that the HSI in adjacent bands is very highly correlated. The inter-band (spectral) correlation tends to be higher than the intra-band (spatial) correlation. This characteristic provides us a probability to compress the HSI by making efficient use of this spectral correlation.

For the compression of HSI, two kinds of correlation can be utilized – spatial correlation and spectral correlation. The spatial correlation has been readily exploited by various image compression techniques for many years. So most research should focus on inter-band decorrelation. Up to now, the inter-band decorrelation algorithms can be divided into three groups: transform-based, VQ-based and prediction-based algorithms. Prediction-based algorithms have the advantages of simple and easy to realize. So many prediction-based algorithms were proposed in the last few years. G. P. Abouleman proposed DPCM and adaptive DPCM to decorrelate the correlation between bands[3]. Jarno Mielikainen proposed clustering DPCM[4]. This method can get lower prediction residual than traditional DPCM based methods. Although DPCM is a good prediction method, it only uses the
previous band. In order to overcome the drawback, Bidirection Prediction (BP) is proposed[5]. Furthermore, Recursive BP (RBP) is proposed by Zhang, which can get better prediction result than both BP and DPCM algorithms[6].

Traditional prediction methods have a lot of advantages. But all the prediction algorithms above, including DPCM, BP and RBP, have a shortcoming: the prediction parameters can’t change according to the HSI. To overcome it, the linear model of HSI is established, and the best prediction is deduced under the sense of SNR in this paper.

2. Recursive bidirection prediction

To explain the principle of BP algorithm, Figure 1 gives an example of one-dimensional signal by using BP (it can be extended to two-dimensional image). To a given signal sequence, the coding sequence begins with \( f_{R1}, f_{R2}, \) and \( f_{R3} \). These are coded with low distortion and are used reference values. \( f_3, f_2, \) and \( f_1 \) are not predicted by reconstructed one side pixels and are predicted by the reconstructed two side pixels \( f_{R1} \) and \( f_{R2} \). Since the correlation in two side pixels is utilized, the high entropy reduction can be achieved. In addition, owing to the replacement of the reference values, the accumulation of coding noise can be avoided. By differencing the original values with the predicted values in BP, the residual values (dark line in Figure 1) are obtained. Still, the entropy of the residual data is smaller than that of the original data.

It is noted that the distance between two reference values is very important for performances of the compression methods. In fact, the longer the distance is, the higher the compression ratio is. But the long distance will result in serious distortion. Although BP can overcome drawbacks of DPCM method, it dose not fully reduce the entropy. It will be seen that the RBP can obtain much better entropy reduction than both BP and DPCM methods.

The principle of RBP is shown in Figure 2. In this method, not all the pixels \( f_2, f_3, \) and \( f_4 \) are predicted directly by the reconstructed two side reference values \( f_{R1} \) and \( f_{R2} \), but the pixel \( f_3 \) is predicted directly by \( f_{R1} \) and \( f_{R2} \). The residual of \( f_3 \) is coded with low compression ratio and then \( f_3 \) is reconstructed. Next, \( f_2 \) and \( f_4 \) are not predicted by the reconstructed \( f_{R1} \) and \( f_{R2} \). But \( f_2 \) is predicted by the reconstructed \( f_{R1} \) and \( f_3 \), and \( f_4 \) is predicted by the reconstructed \( f_3 \) and \( f_{R2} \). We can get smaller residuals of RBP than that of BP.

![Figure 1. Bidirection Prediction.](image1)

![Figure 2. Recursive Bidirection Prediction.](image2)

In figure 1 and figure 2, \( f_{R1} \) and \( f_{R2} \) are reference bands. Let \( f_i \) is non-reference band. The distance between \( f_{R1} \) and \( f_{R2} \) is \( D \), and the The distance between \( f_{R1} \) and \( f_i \) is \( d \).

\[
\hat{f}_i = f_{R1} + (f_{R2} - f_{R1}) \frac{d}{D} = [f_{R1}, f_{R2}] \begin{bmatrix} \frac{D-d}{D} \\ \frac{d}{D} \end{bmatrix} 
\]

From equation (1), we can see that the prediction parameters are \( \left[ \frac{D-d}{D} \right] \) and \( \left[ \frac{d}{D} \right] \), which are determined by the distance between the non-reference band and the reference band. The parameters don’t change according the band.
3. Optimal RBP

Traditional prediction methods have the advantage of simple and easy to realize, but the result is not optimal. In this section, the linear model of HSI is established, and the best prediction is deduced under the meaning of SNR.

The non-reference band is departed into two parts: the prediction part and the prediction residual:

\[
\hat{f}_i = f_i + n = \begin{bmatrix} f_{i1} \\ f_{i2} \end{bmatrix} + n = \begin{bmatrix} D-d \\ d \\ D \end{bmatrix} + n = F_i \times k_i + n
\]

\(\hat{f}_i\) is the prediction of \(f_i\) and \(n\) is the residual. \(F_2 = [f_{11}, f_{12}] \times k_i = \begin{bmatrix} D-d \\ d \\ D \end{bmatrix} \times k_i = \begin{bmatrix} D-d \\ d \\ D \end{bmatrix}\) is determined by the distance \(d\) and \(D\), and \(k_i\) fulfils nonnegativity constrain and sum to one constrain, which are not necessary in HSI prediction. So the prediction result isn’t optimal.

To get better prediction, we can adjudge the prediction parameters \(k_i\) to get minimum of \(\|n\|^2\).

Minimize \(\|n\|^2 = (f_i - F_i \times k_i)^T \times (f_i - F_i \times k_i)\) \(\tag{3}\)

To get best \(k_i\):

\[
\frac{\partial (f_i - F_i \times k_i)^T \times (f_i - F_i \times k_i)}{\partial k_i} = 0 \tag{4}
\]

\[
\Rightarrow \frac{\partial (f_i - F_i \times k_i)^T}{\partial k_i} \times (f_i - F_i \times k_i) + \frac{\partial (f_i - F_i \times k_i)^T}{\partial k_i} \times (f_i - F_i \times k_i) = 0 \tag{5}
\]

From equation (5), we can get:

\[
F_i^T \times F_i \times k_i = F_i^T \times f_i \tag{6}
\]

Because \(F_2^T \times F_2\) is a symmetric positive definite matrix, it has an inverse matrix:

\[
(F_2^T \times F_2)^{-1} \times (F_2^T \times f_i) \times k_i = (F_2^T \times F_2)^{-1} \times F_2^T \times f_i \tag{7}
\]

\[
k_i = (F_2^T \times F_2)^{-1} \times F_2^T \times f_i \tag{8}
\]

By using the new \(k_i\), we can get lower residual.

The block diagram of this compression system is shown in Figure 3. The system includes three steps: intraband JPEG2000 compression of reference bands; interband ORBP of non-reference bands and intraband standard JPEG2000 compression of the residual images.

![Figure 3. The scheme of optimal RBP based compression.](image)

There are two functions for the reference bands. The first function is that the compressed reference bands are transmitted for decoding in the receiver. The other function is that they are reconstructed for the other non-reference bands to be predicted. The quality of reference bands’ compression is very
important for the quality of the whole system. It is necessary to have high quality reconstructed images in the reference bands.

After the compressed reference bands are reconstructed, they are fed into ORBP decorrelation spectrally. In order to realize this purpose, two parameters must be predecided according to the HSI characteristics. By using the ORBP algorithm, the prediction parameters and the residual data are produced.

In this HSI compression system, the spectral decorrelated residual images are fed into standard JPEG2000 for spatial decorrelation and compression.

The compressed bit stream and prediction parameters are together transmitted. In the receiver, according to received bit stream and prediction parameters, the inverse operations are carried out and reconstructed images can be obtained.

4. Experiments and results

In order to test the usefulness of the proposed algorithm, HSI cube is tested. The characteristics of the images are: spectral resolution is 126 bands; wavelength is from 380 nm to 1800 nm; spatial resolution is 3.5 m x 3.5 m and pixel resolution is 256 x 256 x 2 bytes. Figure 4 shows the 15th band of original image and reconstructed image (the compression method is ORBP).

![Original image (Band 15) vs Reconstructed image (Band 15)](image)

**Figure 4.** The original image and reconstructed image.

In this paper, 6 bands of 126 bands are chosen as reference bands and the distance between two reference bands is chosen as 20. Figure 5 shows the residual entropy of different bands. From this figure, we can see that the ORBP based algorithm can get lower entropy after prediction.

In order to evaluate the performances of the new algorithm, we use two parameters: Compression Ratio (CR) and Signal to Noise Ratio (SNR). Because of the importance of reference band, the rate of reference bands is 4 bpp (both in BP, RBP and ORBP). To get the same compression ratio, the rate of non-reference bands is 0.2 bpp in BP and RBP, and the rate of non-reference bands is 0.19995 bpp in ORBP (the prediction will take some storage). The reconstructed SNR is shown in Figure 6. The average SNR is 36.8000 dB in RBP and the average SNR is 46.0738 dB in ORBP.

This paper proposes a novel ORBP/JPEG2000 method for hyperspectral image compression. The compression method is mainly based on ORBP scheme for spectral decorrelation followed by the standard JPEG2000 algorithm for coding the resulting decorrelated residual images. The results of the computer simulation on the AVIRIS images show that this new method has the outstanding objective and subjective quality even at compression ratio as high as 42:1. When comparing the new method with RBP method, the reconstructed images in the new method matches very well with the visual information and the performances are much better than that of RBP.
Figure 5. Residual entropy of different bands.

Figure 6. SNR of different bands.

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