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Scalable Compression Method for Hyperspectral Images

Ganeshraj P. and Sivasankar A.
Department of Information & Communication, Engineering, Anna University Chennai Regional, Center Madurai Madurai, INDIA

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Abstract

In this paper, we propose a low complexity compression method to hyperspectral images using distributed source coding (DSC). DCT was applied to the hyperspectral images. Set-partitioning-based approach was utilized to reorganize DCT coefficients into wavelet like tree structure. Cellular automata (CA) for bits and bytes error correcting codes (ECC) to high through put rate. The CA-based scheme can easily be extended for correcting more than two byte errors. Its performance is comparable to that of the DSC scheme based on informed quantization at low bit rate.

Keywords: Index Terms—discrete cosine transform (DCT), distributed source coding (DSC), hyperspectral images. Cellular automata (CA).

Introduction

Hyperspectral imaging, like other spectral imaging**,** collects and processes information from across the electromagnetic spectrum. Hyperspectral images are spectrally over determined; they provide ample spectral information to identify and distinguish between spectrally similar (but unique) materials. Hyperspectral remote sensing is used in a wide array of applications. It is used in agriculture, mineralogy, surveillance, physics, chemical Imaging. Because an entire spectrum is acquired at each point, the operator needs no prior knowledge of the sample.

Hyper-spectral images consist of huge amount of data. This paper presents compression technique developed specifically for these images. This technique explores unique characteristics of the hyper-spectral images and incorporates them into the compression. The need for compression arises from the fact that these images consist of a huge amount of data and the satellites need to transmit them to the ground. The Terra satellite alone generates approximately 918 giga bytes (GB) of data each day.

In general, there are two kinds of image compression: lossless and lossy compression. Lossless compression is when the original image and the decompressed image are the same. Lossy compression is when there is difference between the original image and the decompressed image. The efficiency of the compression is usually measured by the compression ratio. Two ways to measure the difference between the original image and decompressed image, one is mean squared error (MSE), and the other is peak signal to noise ratio (PSNR).

Compression of multispectral and hyperspectral images has recently received a lot of attention[1]. Hyperspectral image compression based on JPEG2000 with principal component analysis (PCA) provides spectral decorrelation as well as spectral dimensionality reduction. The rate distortion performance is improved by this method. Hyperspectral image compression based on 3D produce high compression ratio than JPEG2000. The embedded coding of Set Partitioned Embedded block (SPECK) algorithm is modified and extended to three dimensions. The resultant algorithm, three-Dimensional Set Partitioned Embedded blocks (3D-SPECK)[2]. Hyper spectral image compression based on JPEG2000 and 3-D transform, have excessive complexity. Hyper spectral image compression requires low complexity encoder because it is usually completed on board where the energy and memory are limited. Another desirable feature for multispectral images compression is progressive reconstruction. Such feature is very useful when users are browsing the image data for specific applications[3]. We can employ distributed source coding (DSC) principle to compress them efficiently at a lower cost. Compared with conventional source coding schemes, the DSC method can shift the complexity from encoder to decoder.

We put forward a low-complexity DSC scheme for onboard compression of hyper spectral images[4]. In particular, our method is conducted in discrete cosine transform (DCT) domain, rather than WT domain. The auxiliary reconstruction is applied to improve the reconstruction quality at the decoder. According to the characteristics of DSC, we make further use of the side information to reconstruct DCT coefficients, reducing the quantization errors. Furthermore, we use the Gray code for the refinement bits of DCT coefficients which can significantly and efficiently improve the correlation between the source and the side information.

In this paper CA-based byte error correcting code has been proposed for high through put. Design scheme for CA-based byte error correcting code has been reported in a VLSI architecture for cellular automata based Reed-Solomon decoder This requires less hardware compared to the existing techniques used for RS code[5]. A design and implementation of CA-based RS (32, 28) encoder and decoder has been presented in Design and implementation of Rs (32, 28) encoder and decoder using cellular automata. The design and implementation of an improved double byte error correcting code using CA has been proposed. It also reports the extension of the scheme to detect/correct more than two byte errors. CA-based proposed design requires much less hardware and power. Our proposed scheme is suitable for codes having smaller number of error correction capability and smaller data word length.

Methodology

From the survey of previous works, Hyperspectral image compression of many algorithms, including those based on JPEG2000 and 3-D transform, have excessive complexity. We proposed; employ distributed source coding (DSC) principle to compress them efficiently at a lower cost. Compared with conventional source coding schemes, the DSC method can shift the complexity from encoder to decoder.

Distributed Source Coding (DSC): Source coding is a way to remove the uncontrolled redundancy occurring in the original information source so as to reduce the bandwidth of signal for it to be accommodated in the channel. For example, we hardly see the difference of consecutive frames in a slowly varying video sequence. Therefore, we can predict most pixels in the next frame by observing the first frame, such that the most pixels in next frame are redundant which can be removed hence compress the source. Source coding can be either lossless or lossy. Lossless source coding is the compression of a signal where the decompression gives back to the original signal. Slepian-Wolf coding is a case of lossless coding[6]. Lossy source coding achieves greater compression by throwing away some information of the signal that doesn't matter. Wyner-Ziv coding is a case of lossy coding. The problem of source coding becomes significantly more interesting and challenging in network. Several new scenarios arise: i. Different parts of the source information may be available to separate encoding terminals that cannot cooperate. ii. Decoders may have access to additional side information about the source information or they may only obtain a part of the description provided by the encoders.

Source coding with side information known as distributed source coding. Distributed source coding of correlated sources refers to the compression of the outputs of two or more physically separated correlated sources which do not communicate with each other (hence distributed coding). These sources send their compressed outputs to a central point (e.g., the base station) for joint decoding Distributed source coding is a new coding paradigm based on two information theoretic results: Slepian-Wolf and Wyner-Ziv theorems.

According to the Slepian-Wolf Theorem, the achievable lossless compression rate of two independent sources X1 and X2 are same even they encoded separately but decoding jointly. The theorem was extended to the lossy case by Wyner-Ziv, while the input source X1 is lossy encoded, the second source X 2 called Side Info is available lossless at the decoder. The rate distortion function of X1 is same even the Side Information is known only at the decoder. However in the case of both X 1 and X 2 are lossy encoded, the rate distortion limits have not been solved yet.

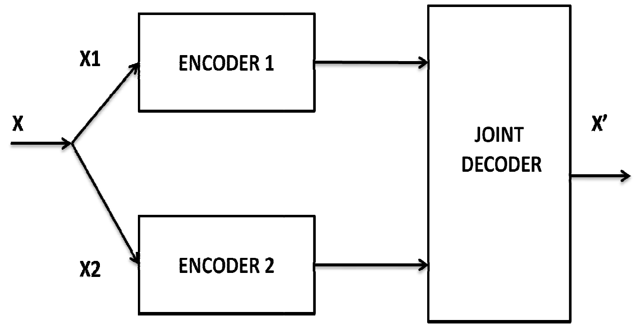

Figure-1
Distributed source coding with separated encoding and joint decoding

The image should be divided into two sources X1, X2 which are encoded separately. The low-pass component of the discrete wavelet composition of the image is used as X2. For X1, a modulo based binning that has error correcting capabilities on edge boundaries is used. Instead of classical source encoding of X1, the pixel values are grouped into bins based on a modulo operation, and decoder finds the value of the syndrome that is closest to the X2.

Consider the figure-1. The input of the true data X, which are X1 and X2 respectively. After the separately encoding of the two noisy observations, the central receiver decodes the two sources jointly. The inputs are encoded with R1 and R2 such that the total rate should satisfy the conditions R1 _ H(X1jX2), R2 _ H(X2jX1) and R1 +R2 _ H(X1;X2), where H(XijXj) is the conditional entropy of Xi given Xj and H(X1;X2) is the joint entropy of X1 and X2.

DSC widely used in hyper spectral imaging, wireless hearing aids, biometrics, image encryption, cognitive radio spectrum sensing.

Block Diagram: Figure 2. Shows the proposed architecture. We divide the hyperspectral images into several groups. Each group has a key band which is compressed directly by the modified EZDCT. The key band has relative high quality. All the other bands are compressed based on DSC.

The reference band Xi-1 is transmitted by means of the modified EZDCT. In the EZDCT, we employ zero tree quantizer in SPIHT algorithm and SPIHT coder rather than EZW coder. Employ zero tree quantizer in SPIHT algorithm and SPIHT coder rather than EZW coder. As a result, its reconstructed image Yi-1 is generated and offered at the decoder side.

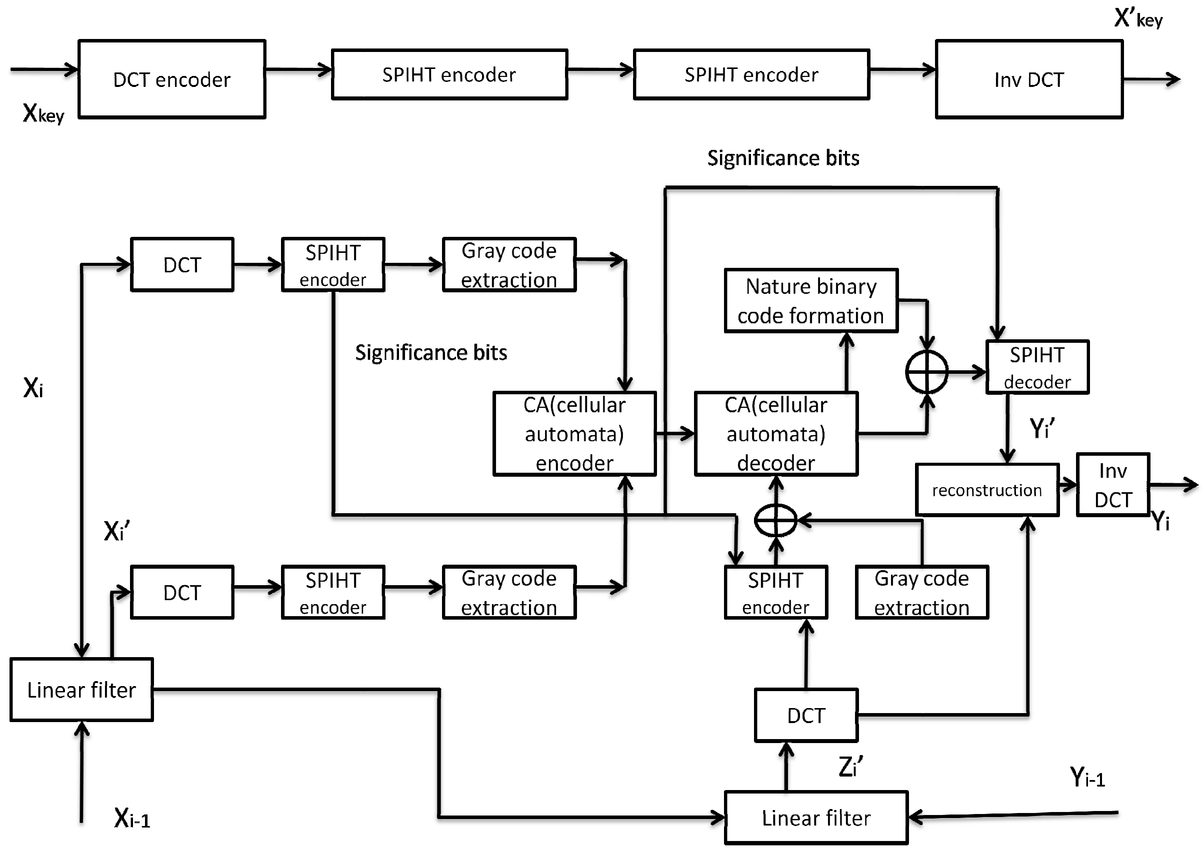

Figure 2

DSC-based coding architecture for hyperspectral images in DCT domain

Here we use CA (Cellular Automata), through this we can get the improved through put, latency (4846, 266) and area. By this we can reduce the number of iterations. The design and implementation of an improved double byte error correcting code using CA has been proposed. It also reports the extension of the scheme to detect/correct more than two byte errors.

CA Based Error Correcting Code: Cellular automata (CA) established novelty for bits and bytes error correcting codes (ECC). The code is very much suited from VLSI design viewpoint and requires significantly less hardware and power for decoding compared to the existing techniques employed for Reed–Solomon (RS) Codes. Also it has been shown that the CA-based scheme can easily be extended for correcting more than two byte errors.

Complexity of RS encoder and decoder increases with the error correcting capability of the codes. Hence many researchers have put their effort to minimize the complexity of RS codec. A high speed systolic architecture for decoding RS code using Berlekamp–Massey (BM) algorithm has been published. RS decoding scheme proposed in "High-speed architectures for Reed-Solomon decoder," and high-speed pipelined degree computation less modified Euclidean algorithm architecture for Reed- Solomon decoders," are more general in the sense that any arbitrary number of errors can be corrected. But both the schemes require complex modules. VLSI system designer always prefers to have simple, regular, modular, and cascadable structure with local interconnection for reliable and high speed operation of the circuit. It has been found that these parameters are supported by local neighborhood CA. CA-based byte error correcting code has been proposed. The proposed design of CA requires less hardware compared to the existing techniques used for RS code. An improved double byte error correcting code using CA has been proposed.

C.A Encoder: In encoder, check byte Cb is generated by running the CA for N cycles while sequentially feeding the N information bytes using the expression.

$$C_b = T^b D_{N-1} \oplus T^{b(2)}[D_{N-2}] \oplus \ldots \oplus T^{b(N)}[D_0]$$

where 0<=b<=3 and T is the characteristic matrix of a 8-cell maximum length CA. The block diagram of CA-based (255, 251) encoder is shown in Fig.3.The four check bytes C0,C1,C2,C3 are generated by running CA-I, CA-T^2 , CA-

T^3CA-Tfor 251 clock cycles, while sequentially feeding 251 information bytes (starting from D0 up to D250). In the encoder block diagram CA-I is a 8-bit uniform CA with rule. 204 and CA-T^b is a 8-bit CA with characteristic matrix T^b, where (0<=b<=3).

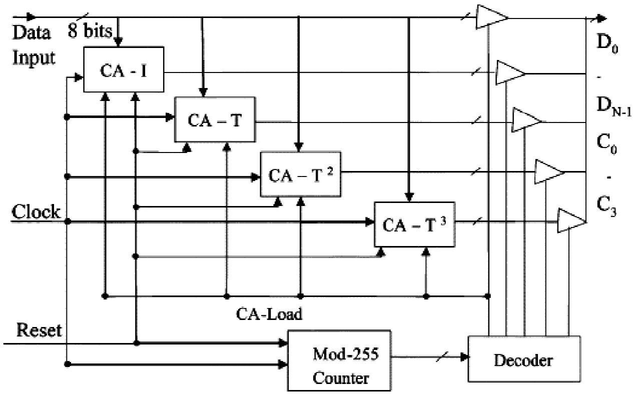

Figure-3
C-A based encoder

C.A Decoder: The decoder consists of four modules: syndrome generator, error location identification block, error magnitude computation block, and error correction block. The syndrome corresponding to the b th check byte Sb is

$$S_b = C_b \oplus C'_b \;\; 0\leq b \leq 3$$

Where Cb is the bth received check byte and C'b is the bth check byte recomputed from the received information bytes. The architecture of syndrome generator is *similar* to that of the encoder. In syndrome generator, CA-I, CA-T , CA-T^2, CA-T^3are allowed to run for 251 clock cycles to compute check bytes C'0,C'1,C'2,C'3. These are XOR-ed with the received check bytes C0, C1, C2, and C3 respectively, to generate the syndrome bytes S0, S1, S2, S3. Generated four syndromes are stored in four registers, which will be used to locate and correct the errors. Suppose Ek and Et are the errors in kth and lth information bytes, then the corresponding syndrome equations are

$$S_b = T^{b(i)}[E_k] \oplus T^{b(j)}[E_j]$$

Where 0<=b<=3,i+k=N, and j+l=N. From the four syndrome equations, error locations k=N-I, and l=N-j are determined using the following equations:

$$T^i[S_2] \oplus S_3 = T^{2j}(T^j[S_0] \oplus S_1)$$
$$T^{2i}[S_1] \oplus S_3 = (T^{2i}[S0] \oplus S_2)$$

Results and Discussion

We have input hyperspectral image. The input image is divided into two parts of process in encoder side. First DCT compression is applied to the image. DCT separates images into parts of different frequencies where less important frequencies are discarded through quantization and important frequencies are used to retrieve the image during decompression. Then SPIHT process is applied to the image.

The Cellular Automata (CA) is applied to image for error correcting process. CA based scheme can easily be extended for correcting more than two bytes error. The input image is displayed in below with file size in terms of Kbytes.

File Size: 1054734

Figure-4
Input image

After CA encoder the image is get into CA decoder. Then SPIHT decoder and Inv DCT process applied to the image. The output compressed image is displayed in below with file size.

File Size: 73483

Figure-5
Output image

The following table shows the MSE (Minimum Square Error) and PSNR (Peak Signal to Noise Ratio) status.

Table-1
MSE and PSNR

MSE	5.1733	4.5645	1.3011
PSNR	40.9931	41.5368	46.9878

Conclusion

We have proposed a DCT-based CA - DSC scheme for hyperspectral images with lower complexity. Due to the auxiliary reconstruction and the modification of transform, our proposal is very competitive, compared with other CA – DSC based coding methods for hyperspectral images. Also, our scheme has the characteristics of ROI coding and progressive image coding. Therefore, the low-complexity CA - DSC based scheme with auxiliary reconstruction is feasible for hyperspectral image compression.. In future the novel algorithm has to reduce the power consumption by as much as without performance loss, while the degradation in clock speed is negligible, and also this concept can be with implementation on our field-programmable gate-array (FPGA)-based prototyping platform.

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