Lossless Compression for Space Imagery in a Dynamically Reconfigurable Architecture

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Abstract. This paper presents a novel dynamically reconfigurable hardware architecture for lossless compression and its optimization for space imagery. The proposed system makes use of reconfiguration to support optimal modeling strategies adaptively for data with different dimensions. The advantage of the proposed system is the efficient combination of different compression functions. For image data, we propose a new multi-mode image model which can detect the local features of the image and use different modes to encode regions with different features. Experimental results show that our system improves compression ratios of space image while maintaining low complexity and high throughput.

1 Introduction

Advances in remote sensing facilities generate massive amounts of data. For instance, SAR (Synthetic Aperture Radar) and the LANDSAT can produce hundreds of gigabytes of data per day, not to mention the 224 bands hyperspectral image from AVIRIS (Airborne Visible/Infrared Imaging Spectrometer). These data are transmitted to the Earth for further processing. However, the data volume is often several times larger than the transmission capacity of the downlink circuit, which limits the scientific data return from the spaceborne instruments. This is known as the "Bandwidth vs. Data Volume" challenge for modern spacecraft [1]. An effective solution to this problem is compression. As space data is costly and subject to processing, all the information in the data should be preserved. Therefore, lossless compression is necessary in space applications.

There are various kinds of data that need to be sent from spacecraft to the Earth, such as 1-D general data, 2-D image data, 3-D multispectral image data or video, etc. These data are likely to be transmitted along the same physical channel. Therefore, a system that can compress different types of data with real-time adaptation is of interest to space applications. The Consultative Committee for Space Data Systems (CCSDS) recommended an ASIC device PRDC (Payload

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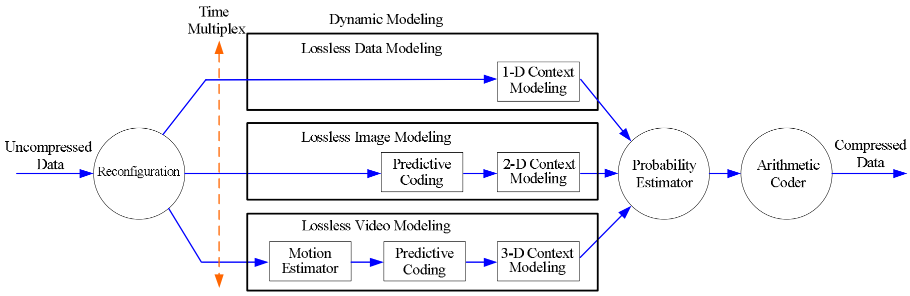

Fig. 1. Architecture of the Lossless Compression System

Rice Data Compressor) [2] for 1-D data, and NASA proposed a FPGA device [3] based on the LOCO algorithm [4] for 2-D image compression. However, in terms of compression ratios, there is still a gap between the performance of hardware and software-based algorithms. Examples of the latter include the context-based PPMZ [5] for 1-D data, and CALIC [6] for 2-D data.

To bridge the performance gap between software and hardware algorithms, and to meet the challenge of data transmission, we propose a reconfigurable architecture targeting to FPGA devices for lossless compression of various types of data from space imagery. Fig. 1 shows the architecture of the system, which consists of four modules: reconfiguration, dynamic modeling, probability estimator and arithmetic coder. The novelty of our proposed system is to effectively combine the statistical models for different data types with the reconfiguration technique. We design three hardware amenable models dedicated to each type of data in the dynamic modeling module. These models share a similar structure, which utilizes contexts, a common probability estimator and arithmetic coder. The reconfiguration technique takes advantage of this feature and efficiently reallocates the hardware resources to execute only the required functionality, in order to minimize the silicon requirements and power consumption. The switching between different models is done adaptively according to the incoming data type. Experimental results show that we achieve superior compression ratios to other state-of-the-art schemes while still keep the system complexity low.

The rest of the paper is organized as follows. In Section 2 we introduce the reconfiguration module. In Section 3 we explain the details of the dynamic modeling, followed by the probability estimator and arithmetic coder in Section 4. We show the performance comparison result with other current hardware amenable algorithms in Section 5 and conclude our work in Section 6.

2 Reconfiguration

Our proposed system is a real-time processing system that encodes and decodes data on the fly. As illustrated in Fig. 1, the reconfiguration module works as the brain of the system, controlling the activities of the dynamic modeling and probability estimator. It detects the data type of the incoming data by examining their file extensions or headers, and activates the corresponding hardware resources in other modules during the coding process. To be more specific, we use a Leon3 processor as a reconfiguration controller, which is connected with the dynamic modeling module, probability estimator, and an external memory. Once a function is requested, the controller loads the configuration data from the memory to the dynamic modeling module and probability estimator. This technique integrates all the modules into a system and reuses the hardware resources, resulting in a reduced amount of resources usage and power consumption.

3 Dynamic Modeling

The dynamic modeling module carries out the major algorithmic tasks. The three models in this module are all context based. *Context*, here means the previously seen symbols in 1-D data, or the surrounding symbols of the current symbol in 2-D or 3-D data.

3.1 Lossless 1-D Data Modeling

Lossless data modeling deals with 1-D data. It is based on the PPMH algorithm implemented in the high-speed hardware compressor Byacom [7]. According to the variable-order Markov modeling mechanism, the variable-order contexts are formed and searched in a context tree, which is built dynamically as more data is seen. The context of the current symbol is stored in a FIFO, whose length is configurable and depends on the maximal model order. The main part of the model is implemented as a context tree, which enables fast search operations with low complexity. A single-cycle reset and rescale of the tree are also implemented to speed up the operation of the model. Once a context is matched, the context area address and the context symbols are sent to the probability estimator.

3.2 Lossless Image Modeling

Lossless image modeling handles image or any data which has two-dimensional correlations. We propose a segmentation-based lossless image model. Segmentation, here means partitioning of an image into multiple regions according to its features. We use this idea to group pixels with similar features and use different modes to compress them. A new ternary-mode is proposed to detect and encode the edges, while the run-length coding [4] is adopted to encode the homogeneous regions. The rest of the image, mostly the texture regions, is compressed with a regular-mode, which is based on the Gradient-Adjusted Prediction (GAP) from CALIC [6] but is simplified. As the mode selection is made by adaptive online checking of neighboring symbols, no side information is transmitted.

We identify certain conditions for entering each mode. If the four nearest symbols of the current symbol are the same, a homogeneous region is assumed and the run-mode is triggered. If the current symbol is identical to its previous symbol, the symbol occurrence, called *run*, increases by one; otherwise "run"

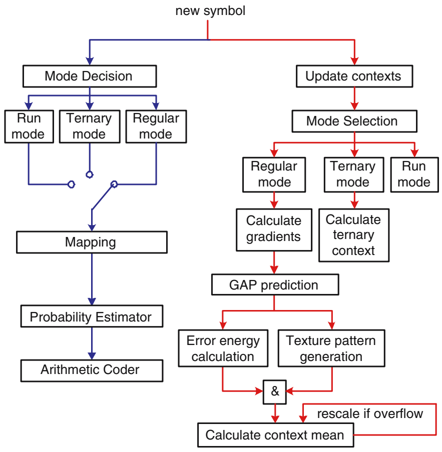

Fig. 2. 2-D data modeling architecture

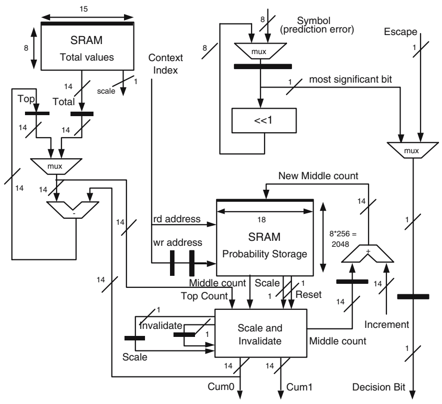

Fig. 3. Architecture of the probability estimator

stops and the current *run length* is encoded. In regions where edges are present, we examine if there are no more than three distinct symbol values in a small neighborhood of the current symbol and the ternary-mode is triggered. Thus only four symbols are needed to encode this group of symbols and lower entropy can be obtained. When the entry conditions for run-mode or ternary-mode cannot be met, or when coding in other modes fails, the regular mode is used.

Fig. 2 illustrates the dataflow of the image model. The implementation is achieved with two pipelines running in parallel. Line 1, indicated by the flow on the left, operates on the current symbol and yields the prediction error with the selected mode for the probability estimator; Line 2, indicated by the flow on the right, calculates the prediction value and context index for the next symbol under the selected mode. Since complicated calculation on coefficients are not needed, and simple division is done by small lookup table, this model is hardware amenable. Note that this model is the base of the video model and can be extended to handle multispectral images. The details of the image compression algorithm is reported elsewhere.

3.3 Lossless Video Modeling

Lossless video modeling compresses data which contains three-dimensional correlations, typically videos or multispectral images. Based on the 2-D model, the video model incorporates the decorrelation in spectral domain and temporal domain. An inter-band prediction is used to exploit the correlation in spectral domain and a switching strategy is designed to switch between intra-band and inter-band prediction, according to which correlation is stronger in the local area. For temporal domain, we intend to use a zero-side-information (no motion vectors) motion estimator to remove redundancy between frames. Implementation details of this model are currently under investigation.

Table 1. Lossless Image Compression Bit Rates (bpp) Comparison

image	CCSDS	PRDC	JPEG-LS	JPEG2000	SPIHT	ICER	proposed
coastal_b1	3.36	3.56	3.09	3.13	3.09	3.07	3.00
coastal_b2	3.22	3.32	2.90	2.97	2.94	2.92	2.84
coastal_b3	3.48	3.68	3.22	3.23	3.21	3.20	3.14
coastal_b4	2.81	2.91	2.41	2.53	2.57	2.55	2.37
coastal_b5	3.16	3.30	2.81	2.94	2.91	2.89	2.79
coastal_b6h	3.02	2.75	2.50	2.60	2.71	2.54	2.52
coastal_b6l	2.35	2.03	1.76	1.96	2.02	1.87	1.84
coastal_b7	3.45	3.66	3.17	3.22	3.17	3.15	3.10
coastal_b8	3.66	3.93	3.42	3.40	3.35	3.31	3.28
europa3	6.61	7.48	6.64	6.52	6.46	6.30	6.42
marstest	4.78	5.39	4.69	4.74	4.64	4.63	4.60
lunar	4.58	5.23	4.35	4.49	4.43	4.40	4.20
spot-la_b3	4.80	5.20	4.53	4.69	4.70	4.56	4.43
spot-la_panchr	4.27	4.87	4.00	4.13	4.11	4.03	3.90
average	3.82	4.09	3.54	3.61	3.59	3.53	3.46

4 Probability Estimator and Arithmetic Coder

The probability estimator is shared by all the models in the dynamic modeling module. Fig. 3 shows a simplified diagram of the probability estimator. It is a SRAM memory where the probability of symbols in each coding context is stored. *Coding context* is defined by the local feature of the data and is used to group symbols in the way that a lower conditional entropy can be achieved. Each coding context is represented by a balanced binary tree with n (n is the alphabet size of the data) nodes associated with each symbol. The values of the tree nodes reflect the symbol occurrence adaptively and are used to calculate the symbol probability. This module maps the probability data into a set of binary decisions (left or right, represented by 0 or 1) from the root to the leaves through each context tree. The binary arithmetic coder is driven by these decision bits and the probability data. It is multiplication-free, resulting in an improved clock ratio of the system. One decision bit is processed per clock cycle, and hence 8 cycles are needed for encoding one byte. More details can be found in [7].

5 Performance Comparison

The experimental result of image compression ratios is presented in this section. We use the 8-bit CCSDS reference image set as test images. As the proposed system is intended for high-speed spaceborne application, test results relevant for this purpose are presented. We compare the proposed scheme with some state-of-the-art low complexity schemes. CCSDS is the current Recommendation for space image compression; PRDC is the CCSDS Rice coder; JPEG-LS is the lossless image compression standard; JPEG2000 [8] is the current standard for lossy to lossless compression; SPIHT [9] is a low-complexity progressive image compressor; ICER [10] is another progressive wavelet-based image compressor. When strip-based and frame-based options are available for these algorithms, the better ones are chosen in this comparison. Table. 1 shows that the proposed system outperforms the others in terms of bit rates. The proposed system processes 1 bit per clock cycle, which is translated into a throughput of 100Mbits/sec on a Xilinx Virtex-4 SX35 FPGA. Results on general data can be found in [7].

6 Conclusions and Future Works

A novel dynamically reconfigurable FPGA architecture for lossless compression of space imagery is presented. The proposed hardware amenable algorithms produce superior image compression ratios and the reconfiguration technique efficiently combines models for different data types with online adaptation. These features make our system suitable for space application. The complete hardware implementation of the system and its extensions is part of our future works.

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