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Lossless Image Compression Using Super-Spatial Structure Prediction Algorithm

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Abstract—In the image compression, the key challenge is to efficiently encode and represent high frequency image structural components such as patterns, edges and textures. In this work, we develop an efficient image compression scheme based on super-spatial prediction of structural units. This so-called similar structure block prediction is motivated by motion prediction in video coding, attempting to find an optimal prediction of structure components within previously encoded image regions.

Keywords—JPEG-LS, super spatial structure prediction, Context-based adaptive lossless image coding (CALIC), image sequence.

I. INTRODUCTION

Since computers play a vital role in solving the complex issues of our daily life, it has applications even in medical diagnostics. This diagnostics includes magnetic resonance imaging (MRI), ultrasound, computed tomography (CT), capsule endoscopy (CE), etc. These diagnostic machines produce their results in the form of sequences of digital images. These sequences require enormous disk space for storage and take more time for transmission over the network. The solution to this problem can be image compression. Since these images are of high importance and any loss of information in them during the compression process could have greater consequences, we need to use the lossless image compression algorithm. There are many state-of-the-art algorithms like CALIC, LOCO-I, JPEG-LS, JPEG20000 to perform image compression in a way that no information gets lost after decompression of the images. JPEG-LS has exceptional coding and computational efficiency and has many lossless image compression algorithms including JPEG 2000. But the super-spatial structure prediction algorithm proposed in has outperformed the JPEG-LS algorithm. This algorithm divides the image into two regions, i.e., structure regions (SRs) and non-structure regions (NSRs). The structure regions are compressed using the super-spatial prediction technique, while the non-structure regions are compressed using CALIC. The idea of super-spatial structure prediction is taken from video coding. A single image consists of different objects and each object consists of many structures. These structures are repeated in many places in a single image. These structure elements include edges, pattern and textures. Despite the fact that the super-spatial structure prediction algorithm has outperformed the state-of the- art algorithms, the drawback is that it deals only with single images and does not perform correlation among the frames in a sequence. Since there is too much correlation among medical sequences, we can achieve a higher compression ratio using Residue coding. The idea of a compression sequence was first adopted for lossless image compression and use for lossless video compression. But the compression ratio was significantly low, i.e., 2.5, which was even less than the compression ratio achieved by some state-of-the-art algorithms for single image compression, the idea of Residue coding was again adopted; nevertheless, this time they used JPEGLS, the state-of-the-art algorithm for single image compression with Residue coding, through this, a higher compression ratio was achieved. However, this ratio can still be further improved by using super-spatial structure prediction technique used for single image compression, hence replacing the JPEG-LS used for the image sequence. Since correlation among medical image sequences is very high, it can be exploited by using single image coding with Residue coding. In this paper, a new technique is proposed for image compression using Residue coding with super spatial structure prediction.

II. SEQUENCE COMPRESSION WITH SUPER-SPATIAL STRUCTURE PREDICTION

A real world scene often consists of various physical objects, such as buildings, trees, grassland, etc. Each physical object is constructed from a large number of structure components based upon some predetermined object characteristics. These structure components may repeat themselves at various locations and scales Fig. 1. Therefore, it is important to exploit this type of data similarity and redundancy for efficient image coding.

The Super spatial prediction borrows its idea from motion prediction Fig.2. In motion prediction Fig. 2(b), we search an area in the reference frame to find the best match of the current block, based on some distortion metric. The chosen reference block becomes the predictor of the current block. The prediction residual and the motion vector are then encoded and sent to the decoder. In super-spatial prediction Fig. 2(a), we search within the previously encoded image region to find the prediction of an image block. The reference block that results in the minimum block difference is selected as the optimal prediction. For simplicity, we use the sum of absolute difference (SAD) to measure the block difference.

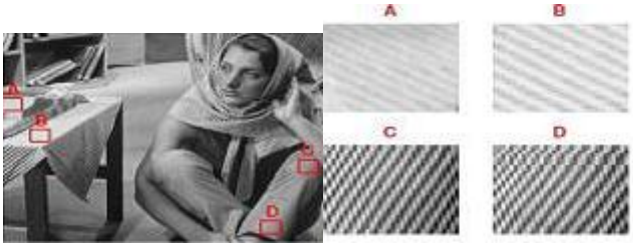

Fig. 1. Example for Super Spatial Redundancies

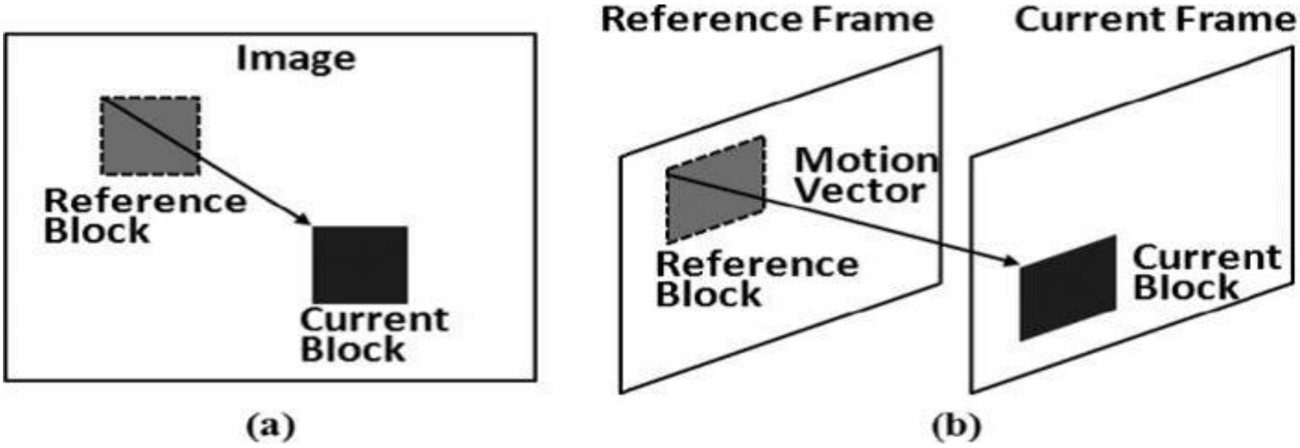

Fig. 2. (a) Super-spatial prediction. (b) Motion prediction in video coding.

As in video coding, we need to encode the position information of the best matching reference block. To this end, we simply encode the horizontal and vertical offsets, between the coordinates of the current block and the reference block using context-adaptive arithmetic encoder. The size of the prediction unit is an important parameter in the super-spatial prediction. When the unit size is small, the amount of prediction and coding overhead will become very large. However, if we use a larger prediction unit, the overall prediction efficiency will decrease. In this work, we attempt to find a good trade-off between these two and propose to perform spatial image prediction on block basis.

A. *Image Block Classification*

A block-based image classification scheme is used here. The image is partitioned into blocks of 8x8. We then classify these blocks into two categories: structure and non-structure blocks. Structure blocks are encoded with super-spatial prediction. Non structure blocks are encoded with conventional lossless image compression methods, such as CALIC.

B. *Estimation of Threshold*

The threshold is required while comparing the current block with the previous encoded region. This threshold value should be so decided that it will give best compression performance.

C. *CALIC*

The Context Adaptive Lossless Image Codec (CALIC) scheme uses both context and prediction of the pixel values. CALIC employs a two-step (prediction/residual) approach. In the prediction step, CALIC employs a simple new gradient based non-linear prediction scheme called GAP (gradient-adjusted predictor) which adjusts prediction coefficients based on estimates of local gradients. Predictions then made context-sensitive and adaptive by modelling of prediction errors and feedback of the expected error conditioned on properly chosen modelling contexts. The modelling context is a combination of quantized local gradient and texture pattern, two features that are indicative of the error behaviour. The net effect is a non-linear, context-based, adaptive prediction scheme that can correct itself by learning from its own past mistakes under different contexts.

CALIC encodes and decodes images in raster scan order with a single pass through the image. The coding process uses prediction templates that involve only the previous two scan lines of coded pixels. Consequently, the encoding and decoding algorithms require a simple double buffer that holds two rows of pixels that immediately precede the current pixel, hence facilitating sequential build-up of the image.

In the continuous-tone mode of CALIC, the system has four major integrated components: -

- Prediction
- Context selection and quantization
- Context modeling of prediction errors
- Entropy coding of prediction errors

CALIC is a spatial prediction based scheme, in which GAP is used for adaptive image prediction.

III. RESIDUE ENCODING

The implemented image compression scheme is purely lossless; the residues need to be transmitted along with the image. But this will increase the payload size and thus the compression will not be achieved successfully. The residues are encountered in two places: - The CALIC Algorithm and the SAD residues. Arithmetic coding schemes are to be used to transmit the residues to further reduce the size of the overhead data per block.

Arithmetic coding is especially useful when dealing with sources with small alphabets, such as binary sources, and alphabets with highly skewed probabilities. It is also a very useful approach when, for various reasons, the modelling and coding aspects of lossless compression are to be kept separate. In arithmetic coding a unique identifier or tag is generated for the sequence to be encoded. This tag corresponds to a binary fraction, which becomes the binary code for the sequence. In order to distinguish a sequence of symbols from another sequence of it has to be tagged with a unique identifier. One possible set of tags for representing sequences of symbols are the numbers in the unit interval (0, 1). Because the number of numbers in the unit interval is infinite, it should be possible to assign a unique tag to each distinct sequence of symbols. In order to do this we need a function that will map sequences of symbols into the unit interval. A function that maps random variables and sequences of random variables, into the unit interval is the cumulative distribution function (CDF) of the random variable associated with the source. This is the function to be used in developing the arithmetic code.

IV. THE COMPLETE ALGORITHM

The complete algorithm used for this lossless image compression scheme can be categorized into two main parts as listed below.

A. *Proposed Encoder*

The original image is subjected to Similar Structure Block Prediction Algorithm. This produces a Lossy Compressed Image and a set of residues. The residues are then encoded using Arithmetic Coding. The Lossy Compressed Image along with the encoded residues forms the compressed data as shown in Fig. 3.

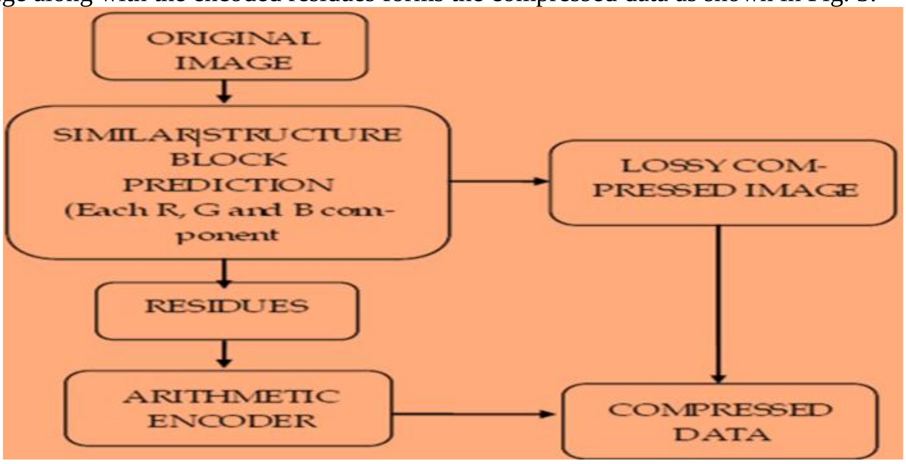

Fig. 3. Proposed Encoder

B. *Proposed Decoder*

The compressed data consisting of Lossy Compressed Image and encoded residues is then given as inputs to the de-coder. The encoded residues are given to the Arithmetic De-coder to obtain the original set of residues which is then added to the Lossy Compressed Image to reconstruct the Final Image as shown in Fig. 4.

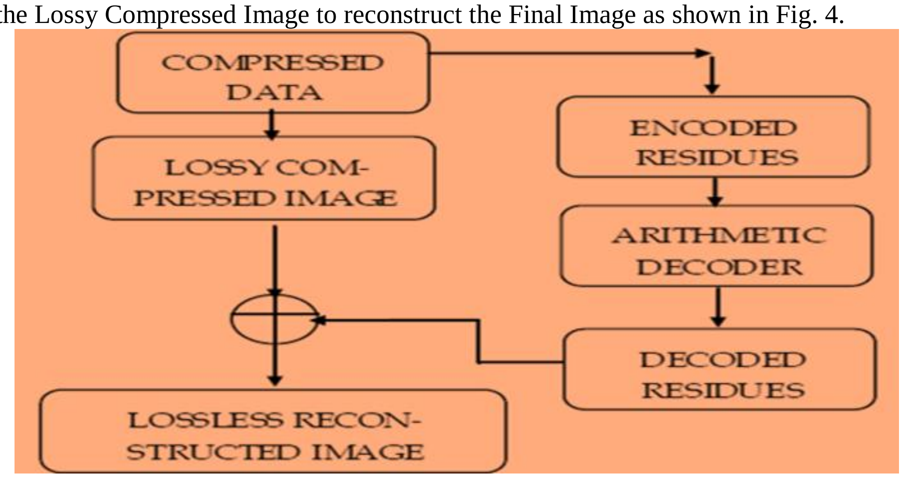

Fig. 4. Proposed Decoder

V. SIMULATION RESULTS

All the simulations were done using MATLAB 7.11 (R2011b) on standard Images (Fig. 5) that have the size of 512x512 pixels like Lena.

a. Original Image b. Compressed Image

Fig. 5. Lena (512x512)

The simulation results by varying threshold values for Lena image are tabulated in Table 1. The best result is obtained for threshold value of 1. The compression performance comparison with CALIC and bit rate saving achieved is tabulated in Table 2. The compression performance comparison with CALIC and bit rate saving achieved is tabulated in Table 3.

TABLE I
RESULTS FOR LENA IMAGE (512X512)

Original Size (kB)	**Lossy Compressed Size (kB)**	**Final Lossless Compressed Size (kB)**	**Threshold**	**PSNR**	**Compression Ratio**
350	21.772	152.0300	0.5	∞	2.3021:1
350	21.090	150.1348	1	∞	2.3312:1
350	19.920	151.6600	2.5	∞	2.3077:1
350	17.830	162.1000	5	∞	2.1592:1

TABLE II
BEST-CASE RESULTS OBTAINED EXPERIMENTALLY FOR LENA IMAGE

Original Size (kB)	**Lossy Compressed Size(kB)**	**Final Lossless Compressed Size (kB)**	**Bit rate of Compressed Image (bpp)**	**Compression Ratio**
350	21.090	150.1348	4.6917	2.3312:1

TABLE III
COMPRESSION PERFORMANCE COMPARISON WITH CALIC

CALIC Bit Rate (bpp)	**SSSP Bit Rate (bpp)**	**Bit Rate Saving (bpp)**
4.8500	4.6917	-0.1583

VI. CONCLUSION

In this endeavour a simple yet efficient lossless image compression algorithm based on structure prediction has been success-fully designed and tested for RGB Colour space. It is motivated by motion prediction in video coding, attempting to find an optimal prediction of a structure components within previously encoded image regions. Taking CALIC as the base code, the image was classified into various regions and they were encoded accordingly. The extensive experimental results demonstrate that the proposed hybrid scheme is very efficient in loss-less image compression, especially for images with significant structure components.

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