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Lossless Image Compression using Super-Spatial Structure Prediction

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***Abstract* – In 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 super-spatial prediction is motivated by motion prediction in video coding, attempting to find an optimal prediction of structure components within previously encoded image regions.**

***Keywords* - Context-based adaptive lossless image coding (CALIC), lossless image compression, structure components, super-spatial structure prediction.**

I. Introduction

The key in efficient image compression is to explore source correlation so as to find a compact representation of image data. Existing lossless image compression [1], [2] schemes attempt to predict image data using their spatial neighborhood [1]. A natural image often contains a large number of structure components, such as edges, contours, and textures. These structure components may repeat themselves at various locations and scales. Therefore, there is a need to develop a more efficient image prediction scheme to exploit this type of image correlation.

The idea of improving image prediction and coding efficiency by relaxing the neighborhood constraint can be traced back to sequential data compression [4] and vector quantization for image compression. In sequential data compression, a substring of text is represented by a displacement/length reference to a substring previously seen in the text. Storer extended the sequential data compression to lossless image compression. However, the algorithm is not competitive with the state-of-the-art such as context-based adaptive lossless image coding (CALIC)[1] in terms of coding efficiency. During vector quantization (VQ) for lossless image compression, the input image is processed as vectors of image pixels. The encoder takes in a vector and finds the best match from its stored codebook. The address of the best match, the residual between the original vector and its best match are then transmitted to the decoder. The decoder uses the address to access an identical codebook, and obtains the reconstructed vector. Recently, researchers have extended the VQ method to visual pattern image coding (VPIC) and visual pattern vector quantization (VPVQ). The encoding performance of VQ-based methods largely depends on the codebook design. These methods still suffer from lower coding efficiency, when compared with the state-of-the-art image coding schemes.

In the intra prediction scheme proposed by Nokia, there are ten possible prediction methods: DC prediction, directional extrapolations, and block matching. DC and directional prediction methods are very similar with those of H.264 intra prediction [3]. The block matching tries to find the best match of the current block by searching within a certain range of its neighboring blocks. This neighborhood constraint will limit the image compression efficiency since image structure components may repeat themselves at various locations.

In fractal image compression [4], the self-similarity between different parts of an image is used for image compression based on contractive mapping fixed point theorem. However, the fractal image compression focuses on contractive transform design, which makes it usually not suitable for lossless image compression. Moreover, it is extremely computationally expensive due to the search of optimum transformations. Even with high complexity, most fractal-based schemes are not competitive with the current state of the art [1].

An efficient image compression scheme based on super-spatial prediction of structure units is presented here. A natural image can be often separated into two types of image regions: structure and non-structure regions. Nonstructure regions, such as smooth image areas, can be efficiently represented with conventional spatial transforms, such as KLT (Karhunen Lòeve transform), DCT (discrete cosine transform) and DWT (discrete wavelet transform). However, structure regions, which consist of high frequency structural components and curvilinear features in images, such as edges, contours, and texture regions, cannot be efficiently represented by these linear spatial transforms. They are often hard to compress and consume a majority of the total encoding bit rate.

Super-spatial structure prediction breaks the neighborhood constraint, attempting to find an optimal prediction of structure components [5], [6] within the previously encoded image regions. It borrows the idea of motion prediction from

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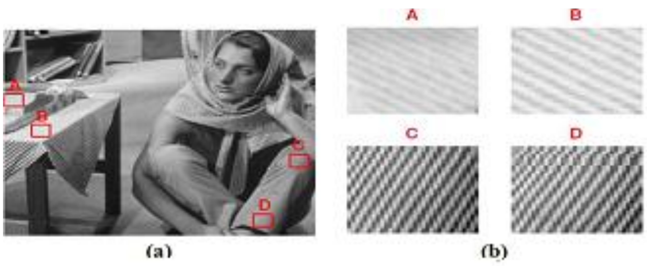
video coding, which predicts a block in the current frame using its previous encoded frames. In order to "enjoy the best of both worlds", a classification scheme is used to partition an image into two types of regions: *structure regions (SRs)* and *nonstructure regions (NSRs)*. Structure regions are encoded with super-spatial prediction while NSRs can be efficiently encoded with conventional image compression methods, such as CALIC. It is also important to point out that no codebook is required in this compression scheme, since the best matches of structure components are simply searched within encoded image regions.

II. 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 [3] 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.



(a) Barbara image. (b) Four image blocks extracted from Barbara
Fig. 1 Example for Super Spatial Redundancies

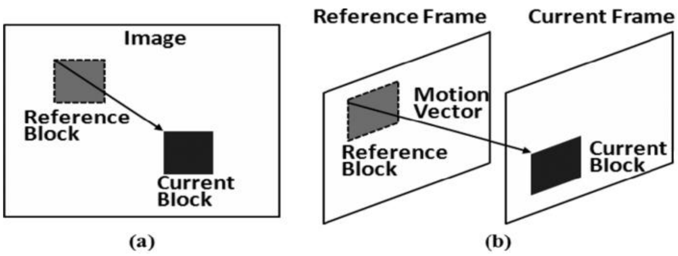


Fig.2. (a) Super-spatial prediction. (b) Motion prediction in video coding.

As in video coding [3], 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 tradeoff 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 nonstructure blocks. Structure blocks are encoded with super-spatial prediction. Nonstructure 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 [1] 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 modeling of prediction errors and feedback of the expected error conditioned on properly chosen modeling contexts. The modeling context is a combination of quantized local gradient and texture pattern, two features that are indicative of the error behavior. 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 [1].

Here GAP prediction is performed on the original image and the prediction error for each block is computed. If the prediction error is larger than a given threshold, then it is considered as a structure block. Otherwise, it is classified as a nonstructure block.

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 [7], [8] 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 modeling 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 Super-spatial Structure 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.

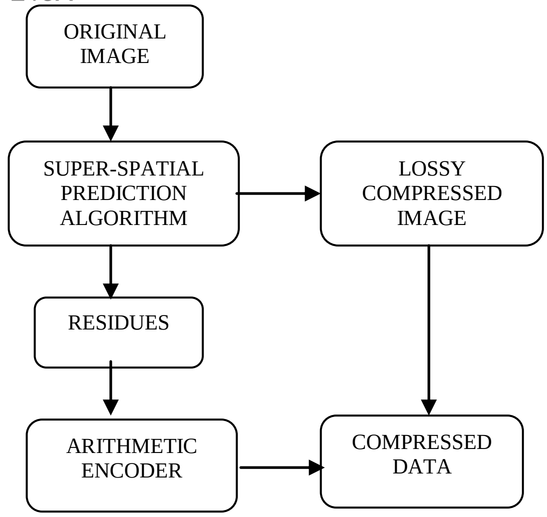


Fig. 3 Proposed Encoder

B. Proposed Decoder

The compressed data consisting of Lossy Compressed Image and encoded residues is then given as inputs to the decoder. The encoded residues are given to the Arithmetic Decoder 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.

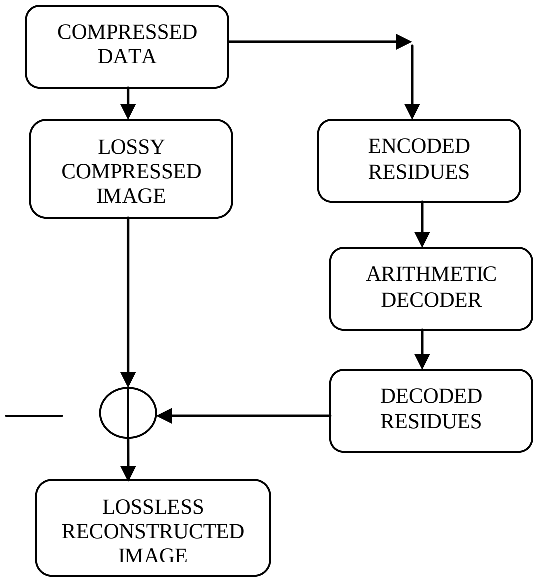


Fig. 4 Proposed Decoder

V. SIMULATION RESULTS

All the simulations were done using MATLAB 7.11 (R2010b) on standard Images like Cameraman (Fig.5.2) that have the size of 256x256 pixels and Baboon (Fig. 5.3), Crowd (Fig. 5.4) and Lena (Fig. 5.1) having the size of 512x512 pixels.

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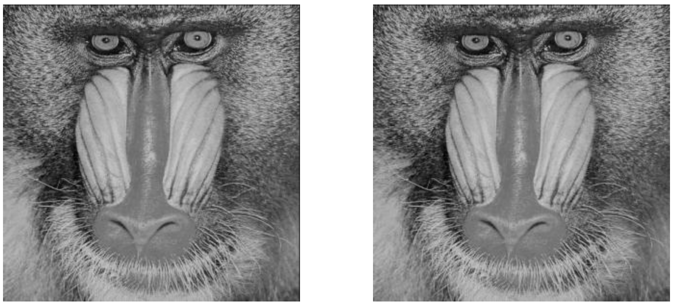
(a) Original Image (b) Lossless compressed image
Fig. 5.1 Lena (512x512)

(a) Original Image (b) Lossless compressed image
Fig. 5.2 Cameraman (256x256)



(a) Original Image (b) Lossless compressed image
Fig. 5.3 Baboon (512x512)

(a) Original Image (b) Lossless compressed image
Fig. 5.4 Crowd (512x512)

The simulation results by varying threshold values for lena image are tabulated in Table I. The best result is obtained for threshold value of 1. Cumulative results for different images are tabulated in Table II. The compression performance comparison with CALIC and bit rate saving achieved is tabulated in Table III.

TABLE I
RESULTS FOR LENA IMAGE(512X512)

Original Size (kB)	Lossy Compressed Size(kB)	Final Lossless Compressed Size (kB)	Thresh-old	PSNR	Compre-ssion 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

Image name	Original Size (kB)	Lossy Compressed Size(kB)	Final Lossless Compressed Size (kB)	Bit rate of Compressed Image (bpp)	Compre-ssion Ratio
Lena	350	21.090	150.1348	4.6917	2.3312:1
Cameraman	85	9.2945	44.1245	5.515	1.9263:1
Baboon	397	27.5391	204.4150	6.387	1.9421:1
Crowd	436	47.8809	227.9100	7.122	1.9130:1

TABLE III
COMPRESSION PERFORMANCE COMPARISON WITH CALIC

Image name	CALIC Bit Rate (bpp)	SSSP Bit Rate (bpp)	Bit Rate Saving (bpp)
Lena	4.8500	4.6917	-0.1583
Cameraman	6.3875	5.515	-0.8725
Baboon	6.6156	6.387	-0.2286
Crowd	7.7500	7.122	-0.6280

VI. CONCLUSION

In this endeavor a simple yet efficient lossless image compression algorithm based on structure prediction has been successfully designed and tested. 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 scheme is very efficient in lossless image compression, especially for images with significant structure components.

VII. REFERENCES

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