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Adaptive Super-Spatial Prediction Approach For Lossless Image Compression

Arpita C. Raut*, Dr. R. R Sedamkar**
*(Department of electronics, viva college of diploma engg. & Tech., Virar (W), India)
** (Department of Computer Engg., Thakur college of Engg. & Tech., Kandivali (E), India)

ABSTRACT
Existing prediction based lossless image compression schemes perform prediction of an image data using their spatial neighborhood technique which can’t predict high-frequency image structure components, such as edges, patterns, and textures very well which will limit the image compression efficiency. To exploit these structure components, adaptive super-spatial prediction approach is developed. The super-spatial prediction approach is adaptive to compress high frequency structure components from the grayscale image. The motivation behind the proposed prediction approach is taken from motion prediction in video coding, which attempts to find an optimal prediction of structure components within the previously encoded image regions. This prediction approach is efficient for image regions with significant structure components with respect to parameters as compression ratio, bit rate as compared to CALIC (Context-based adaptive lossless image coding).
***Keywords* -** Adaptive Super-Spatial prediction approach, Bit Rate, Compression performance, Context-based adaptive lossless image coding (CALIC), structure components.

I. INTRODUCTION

Importance of image compression is increasing day by day with advancing communication technology which becomes a solution for image applications that requires large storage space. The goal of image compression is to represent an image in compact form by minimizing the number of bits as possible without degrading the quality of an image thereby reducing the memory requirement to store images and increases transmission rates.

Image compression can be broadly classified into two categories:
1) Lossless image compression: The original image and the image after compression and decompression are exactly the same because the compression and decompression algorithms are exactly inverse of each other.
2) Lossy image compression create redundancy by discarding some information and then remove it and it is not recoverable therefore lossy compression does not allow the exact original data to be reconstructed from the compressed data.

Image compression algorithms are divided into two main categories according to a method that is used to remove spatial redundancy.

a) Transformation-based image compression
b) Prediction-based image compression

Transform based coding also known as block quantization, exploits spatial frequency information contained in the image to achieve compression. An image is first transforms from its spatial domain representation to a different type of representation using well known transform and then encodes the transformed values (coefficients) so that a large fraction of its energy is compact into relatively few transform coefficients, which are then quantized independently.

Prediction based coding for image predicts a pixel color value based on the pixel color values of its neighboring pixels and encodes the difference between the past data and actual current data to get more efficient compression. As the difference becomes smaller, the information to be encoded becomes smaller as well. Prediction based methods depends on prediction, context modeling and entropy coding. Predictor removes a large amount of spatial redundancy, exploits smooth areas in images. Context modeling further improves prediction by providing the information about pixels context, such as horizontal or vertical edges. Entropy coding removes statistical redundancy, gives a final encoded bit stream.

In image compression the main task is to efficiently represent and encode high frequency image structure components, such as edges, patterns, and textures. Existing lossless image compression schemes such as CALIC [1],[2], LOCO-I[3] can’t predict pixel values very well near edges, boundaries or sharp transitions of pixel values which will limit the image compression efficiency. Hence, there is a need to develop an efficient image prediction scheme to exploit these structure components from the grayscale image.

This paper introduced a new prediction methodology which attempts to predict the high frequency structure components from the grayscale image using adaptive super-spatial prediction approach for lossless image compression which will enhance the accuracy of the prediction and compression efficiency. The motivation behind the proposed prediction approach is taken from motion prediction in video coding, which breaks the neighborhood constraint and finds an optimal prediction of structure components within the previously encoded image regions. As the super-spatial prediction approach is adaptive to compress structure components, an image is classified into two regions: Structure and nonstructure regions using multidirectional GAP (Gradient Adjusted Predictor) [4] which improves speed of the prediction algorithm with the help of parallel implementation. Structure regions (SRs) are encoded using Adaptive super-spatial prediction approach, while non-structure regions (NSRs) are encoded using CALIC. The proposed Adaptive super-spatial prediction approach is designed in such a way that it has good efficiency in terms of compression ratio, compared to existing lossless image compression algorithms, CALIC. Implementation of proposed prediction approach is done in CALIC.

This Adaptive Super-Spatial prediction approach is novel approach because the best matching of structure components are simply searched within previously encoded image regions therefore no codebook is required in this compression scheme.

The structure of paper is as follows. Section 2 represents literature survey. Section 3 represents Adaptive Super-Spatial prediction approach. Section 4 explains the residue encoding scheme used. In section 5, encoder and decoder block diagram of the complete algorithm is given and at the end simulation results, conclusion and future scope.

II. LITERATURE SURVEY

In image compression schemes like vector quantization and sequential data compression [5] where better image prediction and coding efficiency is achieved by relaxing neighborhood constraint. In sequential data compression, representation of a substring of text is done by a displacement/length reference to a substring previously seen in the text.

In lossless image compression by vector quantization, an 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. The encoding performance of VQ-based methods largely depends on the codebook design. Extensions of VQ method are visual pattern image coding (VPIC) [6] and visual pattern vector quantization (VPVQ) [7]. It is observed that, these methods suffer from poor coding efficiency. Therefore these algorithms are not competitive when compared with the state-of-the-art such as context based adaptive lossless image coding (CALIC) [1] in terms of coding efficiency.

JPEG-LS is based on predictive coding technique which is simple, easy to implement, consumes less memory, and is faster than JPEG 2000, though JPEG 2000 supports progressive transmission. JPEG-LS work efficiently on continuous-tone images. CALIC and LOCO-I are the most efficient lossless image compression algorithms. LOCO-I uses same principles to CALIC, but CALIC with arithmetic coding remains considered as a benchmark to which the performance of other compression schemes, gives high compression ratio as compared to LOCO-I and JPEG-LS.

Super-spatial structure prediction [8], [9] is based on motion prediction in video coding which breaks the neighborhood constraint, attempts to find an optimal prediction of structure components within the previously encoded image regions.

In still image compression using texture and non texture prediction model [10], an image classified into texture and non-texture regions by using an Artificial Neural Network (ANN) Classifier. The texture region is encoded with the Similar Block Matching (SBM) encoder and the non-texture region is encoded with SPIHT encoding.

III. ADAPTIVE SUPER-SPATIAL APPROACH OF PREDICTION

This section explains the basic idea of adaptive super-spatial prediction approach for structure region prediction. It is observed that an image consist of many objects and each object consist of significant amount of structural components. These structure components may repeat themselves at various locations and scales. For efficient image compression, it is necessary to exploits this type of image correlation. Figure 1 (a) shows Barbara image and (b) shows four similar structure blocks extracted from Barbara image.

An idea of an adaptive super-spatial prediction approach borrows from motion prediction in video coding where block matching concept is used. In motion prediction as shown in fig. 2, the best match of the current block is search in an area in the reference frame, based on some distortion metric. The chosen reference block from reference frame becomes the predictor of the current block. The prediction residual and the motion vector are then encoded and sent to the decoder.

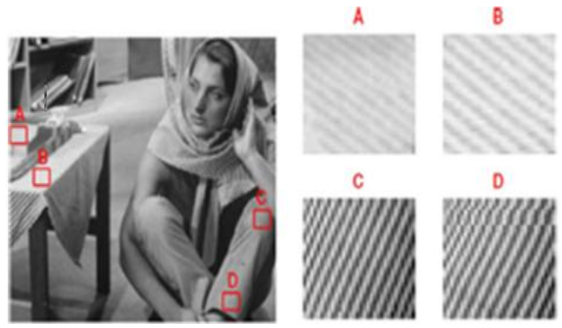

Fig. 1 (a) Barbara image (b) similar structure blocks extracted from Barbara.

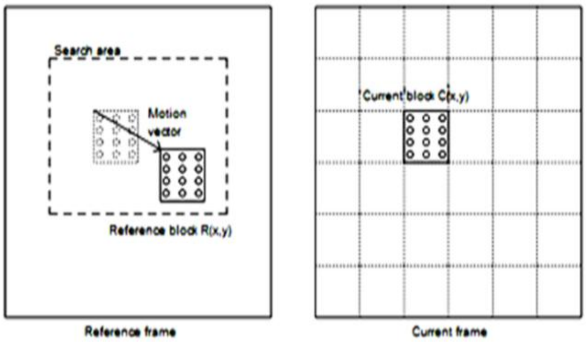

Fig. 2 Motion prediction in video coding.

In adaptive super-spatial prediction approach as shown in fig.3, the prediction of current image block is search within the previously encoded image region. The chosen reference block from previously encoded image region is selected as the optimal prediction for current block. To measure the block difference, the sum of absolute difference (SAD) is used, because it doesn't need multiplication operation which is computationally more attractive for real time application as compared to MSE, as it needs square operation.

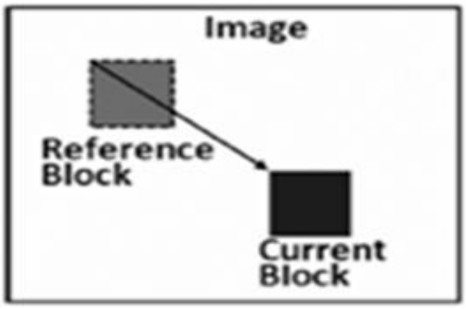

Fig.3 Adaptive Super-Spatial prediction approach .

3.1 Block based image content separation

The 512 x 512 grayscale image is partitioned into blocks of 4x4 blocks. Multidirectional GAP (Gradient Adjusted Predictor) [9] is performed on block based image which reduces computational complexity with the help of parallel implementation and prediction error is calculated. If the prediction error is greater than threshold then the block is considered as structure block otherwise nonstructure block. As per the result of multidirectional GAP prediction, the block classification map (BCM) is maintained. Structure blocks are encoded using Adaptive Super-Spatial prediction approach whereas nonstructure blocks are encoded using conventional lossless image compression method, CALIC.

In multidirectional GAP, The image is divided into four equal parts illustrated in the Fig. 4. We apply the GAP in four different directions. The interesting aspect about multidirectional GAP technique is its parallel implementation.

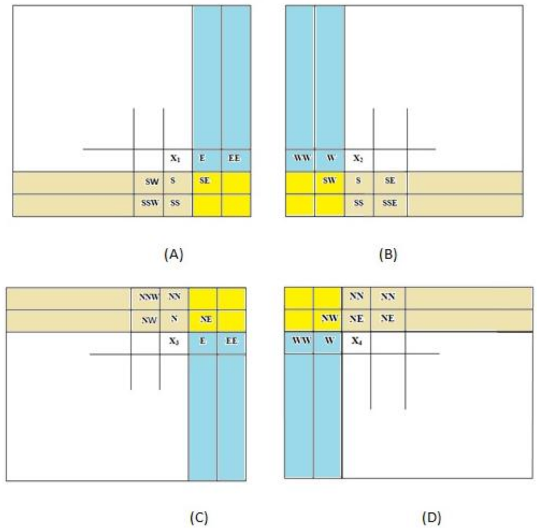

Fig. 4 Four equal parts of predictive template of multidirectional GAP.

3.2 Threshold estimation

As the Adaptive Super-Spatial prediction approach for structure components is motivated from motion prediction in video coding, SAD (Sum of absolute difference) is used to compare current block with previously encoded structure blocks using SAD as shown in equation (1).

$$SAD = \sum_{i=1}^{L} \sum_{j=1}^{L} \mid I[i,j] - \hat{I}[i,j] \mid \qquad (1)$$

where $I[i,j]$ is the pixels of the original block, and $\hat{I}[i,j]$ that of the prediction. Most structure blocks can find its best match in the structure regions [8] which will reduce computational complexity. The threshold value is used for deciding best matching of structure block and its value is decided by experimenting different images and its compression results.

3.3 Implementation in CALIC

CALIC(context based, adaptive lossless image codec) is a spatial prediction based scheme, in which GAP is used for image prediction which uses large number of modeling contexts to condition a nonlinear predictor and make it adaptive to varying source statistics without suffering from context dilution problem. CALIC only estimates expectation of prediction errors conditioned on a large number of contexts rather than a large number of conditional error probabilities.

CALIC uses two step prediction/ residual approach. CALIC is a one-pass coding scheme that encodes and decodes in raster scan order. It uses the previous two scan lines of coded pixels to do the prediction and form the context. CALIC operates in two modes: binary and continuous tone modes. CALIC selects one of the two modes based on local casual template without using any side information. The compression methodologies for these two modes are different. Binary mode is selected when the current locality of input image has no more than two distinct intensity values. Context-based adaptive ternary arithmetic coder is used to encode three symbols, including escape symbols which triggers a return to continuous tone mode

Continuous tone mode has four major components:

1) GAP, gradient-adjusted prediction uses the context gradient information to predict the intensity of current pixel. This step is linear prediction.

2) Context selection and quantization, further remove the correlation between the prediction errors of GAP step by condition the error onto different context error energies. The quantization of context error energies results in totally 8 different error energy levels.

3) Context modeling of prediction errors: Error modeling classifies the errors into different texture catalogs and then use the corresponding sample means to get final prediction. This step makes the final prediction to be nonlinear.

4) Entropy coding of prediction errors using Arithmetic coding or Huffman coding. Generally Arithmetic coding is used for better performance.

IV. PREDICTION RESIDUE ENCODING

Arithmetic coding [11], [12] is a form of entropy encoding used in lossless data compression, especially suitable for small alphabet (binary sources) with highly skewed probabilities. The arithmetic codes generate non-block codes; therefore, a one-to one correspondence between source symbols and code words does not exist. Instead, an entire sequence of source symbols is assigned to a single code word that defines an interval of real numbers between 0 and 1. As the number of symbols in the message increases, the interval used to represent it becomes smaller and the number of bits needed to represent the interval becomes larger. Each symbol in the message reduces the size of the interval according to its probability of occurrence. Arithmetic coding typically has a better compression ratio than Huffman coding, as it produces a single symbol rather than several separate codeword.

V. DESIGN OF PROPOSED WORK

5.1 Encoder

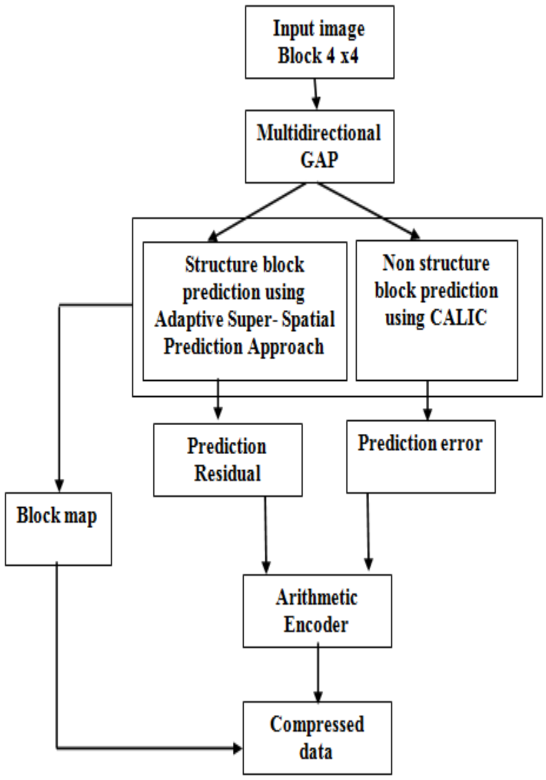

Fig. 5 Encoder of proposed work.

The image is segmented into 4x4 blocks. Multidirectional GAP is applied on image of 4x4 blocks. If the prediction error is greater than threshold then the block will be considered as structure otherwise nonstructure block. Structure blocks are encoded using Adaptive Super-Spatial prediction approach and nonstructure blocks are encoded using CALIC. This produces a block map consisting of addresses of reference blocks and prediction residues and prediction error. This prediction residues and prediction error are given to arithmetic encoder. An encoded residues along with block map forms compressed data as shown in fig. 5.

The output bit stream of the proposed encoder consists of bits for the following major syntax components: bits for non-structure regions, bits for prediction residual of structure blocks, addresses of reference blocks.

5.2 Decoder

The compressed data consisting of block map and encoded residues is given as input to the decoder. The encoded residues are given to the arithmetic decoder to obtain the original set of residues which is then added to block map to reconstruct the final lossless image as shown in fig. 6.

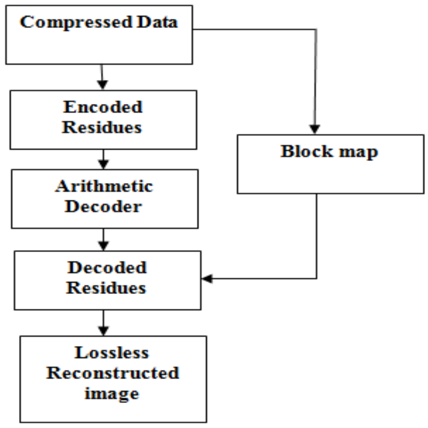

Fig. 6 Decoder of proposed work

VI. Simulation Results and Discussion

All the simulations were done using matlab 7.1 on standard grayscale images like Lena, Barbara, Cameraman, Mandrill having the size of 512x512 pixels in pgm format and 8 bpp in value.

Comparative analysis between proposed work and CALIC is done and result is obtained using compression ratio and bit rate parameters on different images with different structure and nonstructure regions.

Table 1- Compression Performance Comparison with CALIC

Image	Original Size(Kb)	CALIC compressed size (Kb)	Proposed Work compressed size (Kb)	Compression Ratio using CALIC	Compression Ratio using Proposed Work
Lena	256	134	116	1.910:1	2.206:1
Barbara	256	151	131	1.695:1	1.954:1
Camera man	256	104	90	2.461:1	2.844:1
Mandrill	256	137	119	1.868:1	2.151:1

The compression performance comparison with CALIC [1] is tabulated in Table 1. It is clear that Barbara image is compressed by 20 Kb more by proposed work than that of CALIC which consist of more structure components as compared to other images.

From the graph as shown in fig.7, Cameraman image have better compression ratio (2.844:1) as compared to CALIC (2.461:1) than other images.

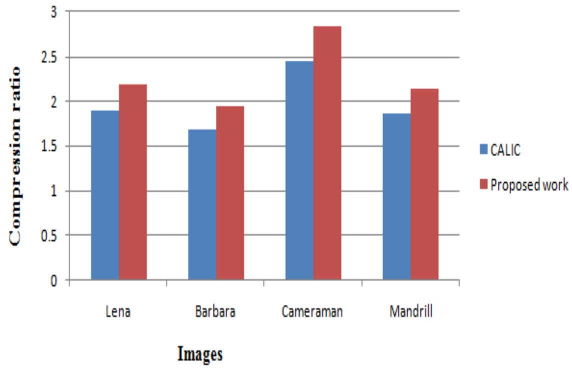

Fig. 7 Comparison of compression ratio.

TABLE 2- Coding Bit Rate Comparison with CALIC

Test Images	CALIC bit rate (bpp)	Proposed work bit rate (bpp)	Bit Rate Saving
Lena	4.18	3.62	- 0.56
Barbara	4.71	4.09	- 0.62
Cameraman	3.25	2.81	- 0.44
Mandrill	4.28	3.71	- 0.57

Table 2 shows comparison of coding bit rate of the proposed work based on new prediction approach with CALIC [1] and calculated bit rate saving.

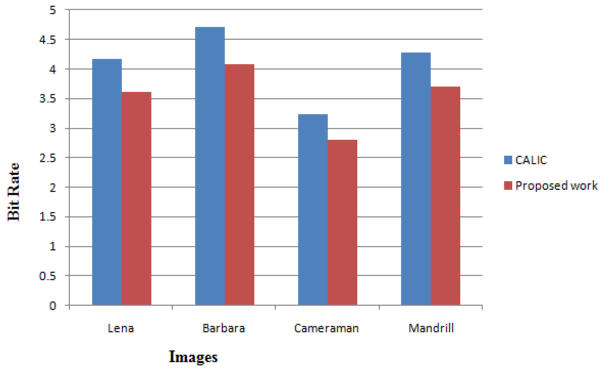

Fig. 8 Comparison of coding bit rate.

From the graph as shown in fig.8 shows performance analysis of proposed work with CALIC using bit rate parameter. In best case, bit rate saving is more in case of Barbara image which consist of more structure components which are repeated at various locations as compared to other images. Therefore proposed prediction approach is efficiently compressed high frequency structure components from the image. Fig. 9 shows original and reconstructed lossless image of Lena.

Fig. 9 a) original and b) Reconstructed Lena Image

VII. CONCLUSION AND FUTURE SCOPE

In this work, an efficient image prediction scheme, called Adaptive super-spatial prediction approach is developed. By using CALIC as the base code, the image was classified into structure and non structure regions using multidirectional GAP with the help of parallel implementation and then they were encoded accordingly. The experimental results indicate that the proposed hybrid scheme of structure and nonstructure region prediction scheme is efficient than existing lossless image compression scheme, CALIC, especially for images with significant structure components

The Adaptive super-spatial prediction approach algorithm has outperformed the state-of-the-art algorithms. As this approach deals only with single image and does not perform correlation among the frames in a sequence and there is too much correlation among medical sequences, therefore in future this study can be further extended to real time applications for video compression in medical images.

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