Dynamic Efficient Prediction Approach for Lossless Image Compression

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ABSTRACT

This paper attempts to predict the high frequency structural components from the grayscale image using dynamic efficient prediction approach as we know the major challenge in image compression is to efficiently represent and encode high-frequency image structure components, such as edges, patterns, and textures. Therefore it is important to learn image structure and adjust the image representation and prediction scheme in an adaptive manner. The idea behind the proposed prediction approach is taken from motion prediction in video coding, attempting to find an optimal prediction of structure components within the previously encoded image regions. We find that 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 : Bit Rate, Block classification map (BCM), Compression Performance , Context-based adaptive lossless image coding (CALIC), Dynamic efficient prediction approach, lossless image compression, structure components.

1 INTRODUCTION

In many important applications of image processing, such as satellite imaging, medical imaging and video where the image size is too large and requires a large amount of storage space for communication in its original form. These factors indicate the need of image compression. Image compression addresses the problem of reducing the amount of data required to represent the digital image which yields a compact representation of an image thereby reducing storage requirements and increase transmission rates.

Compression is achieved by removing one or more of the three basic data redundancies:

1) Coding redundancy, which is presented when less than optimal code words are used;

2) Interpixel redundancy, which results from correlations between the pixels of an image;

3) Psychovisual redundancy, which is due to data that are ignored by the human visual system

Image compression algorithms can be classified in lossy and lossless techniques.

Lossy compression suffers from the loss of some data. Thus, repeatedly compressing and decompressing an image results in degradation of image quality. An advantage of this technique is that it allows for higher compression ratio than the lossless .On the other hand, lossless compression reduces the number of bits required to represent an image such that the reconstructed image is identical to the original one on a pixel-by-pixel basis. Choosing which of these two categories depends on the application and on the compression degree required.

Need for lossless compression of large amounts of data requires speed and efficiency, so prediction based algorithms are chosen before transform-based algorithms. Prediction based coding estimates a pixel value based on the pixel values of its neighboring pixels. Prediction based algorithms rely on prediction, context modeling and entropy coding. Prediction is the first and the most important step which removes a large amount of spatial redundancy. Prediction based algorithm are simple and fast, proven to be effective for lossless image compression.

The key in efficient image compression is to explore source correlation so as to find a compact representation of image data. Spatial image prediction has been a key component in efficient image and video compression [1], [2]. The existing lossless image compression schemes such as CALIC and LOCO [1], [2] attempt to predict image data using their spatial neighborhood which will limit the image compression efficiency. 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.

This paper is concerned with lossless compression using the prediction approach for grayscale images. Prediction based coding is a compression method used for text and image compression. It encodes the difference between the current data estimation derived from past data and actual current data to attain more efficient compression. The degree of efficiency depends very much on the accuracy of the estimation as the difference becomes smaller, the information to be encoded becomes smaller as well.

One of problems of prediction based coding is that it cannot

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estimate pixel values very well near edges, boundaries, or when there are sharp transitions of pixel values. This is because prediction based coding relies on the similarities of neighboring pixels for the prediction and, therefore, the dissimilarities of pixel values near edges or boundaries can adversely affect the accuracy of the prediction of the pixel values. The work presented here is the development and implementation of prediction approach to compress high frequency structure components such as edges, patterns and structures from the grayscale image for lossless image compression which will improve the compression efficiency. This Prediction approach breaks the neighborhood constraint, attempting to find an optimal prediction of structure components within the previously encoded image regions to give higher prediction accuracy. It borrows the idea of motion prediction from video coding, which predicts a block in the current frame using its previous encoded frames. The proposed approach is designed to have good efficiency in terms of compression ratios, compared to existing lossless image compression algorithms. We have implemented proposed prediction approach in CALIC.

As the proposed approach is attempting to predict structure components from the image, we also proposed a classification scheme to segment an image in into two types of regions: structure regions (SRs) and nonstructure regions (NSRs). Structure regions are encoded with dynamic efficient prediction approach while NSRs can be efficiently encoded with conventional image compression method, 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. Our extensive experimental results demonstrate that the proposed prediction scheme is competitive and even outperforms the state-of-the-art lossless image compression methods.

The rest of the paper is organized as follows. Literature review is presented in section 2, The Proposed approach of prediction for lossless image compression is presented in Section 3, where an optimal prediction of structure components is done within the previously encoded structure regions and prediction of nonstructure components areas are encoded using CALIC. Section 4 explains the residue encoding scheme used which helps in retrieving the lossless image at the decoder. In section 5, the block diagram of the complete algorithm is given and at the end simulation results, conclusion and future scope.

2 Literature Review

The idea of improving image prediction and coding efficiency by relaxing the neighborhood constraint can be traced back to sequential data compression [3] 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) [4]. The encoding performance of VQ-based methods largely depends on the codebook design. To our best knowledge, 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 [5]. 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 [6], 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].

We observe that Nonstructure regions, such as smooth image areas from the image, 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 structure 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.

There are several lossless image compression algorithms which have been developed based on spatial prediction method. JPEG-LS is an example of the predictive coding approach which works well on continuous-tone images. It is one of the most popular lossless image compression algorithms. Unlike the previous JPEG compression, which is lossy compression using the Discrete Cosine Transform method (DCT), JPEG-LS is not complex and works well with gray scale images. However, its performance is not as impressive when applied to indexed color or color-map images. But CALIC remains useful as a benchmark to which the performance of other compression schemes can be compared. As expected, CALIC with arithmetic coding performed the best, on average, for all the images in this study. CALIC gives high compression in a reasonable time, whereas JPEG-LS is nearly as effective and very fast.

Super-spatial structure prediction breaks the neighborhood constraint, attempting to find an optimal prediction of structure components [7], [8] within the previously encoded image

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regions. It borrows the idea of motion prediction from video coding, which predicts a block in the current frame using its previous encoded frames.

3 Proposed Approach of Prediction

This section explains the basic idea of proposed prediction approach and how it can be used for efficient image compression.

We observe that a natural image often consist of significant amount of structural components which evolve slowly from regions to regions. These structure components may repeat themselves at various locations and scales as shown in fig.1.It can be seen that they share very similar structure characteristics. Therefore, it is important to exploit this type of data similarity and redundancy for efficient image coding.

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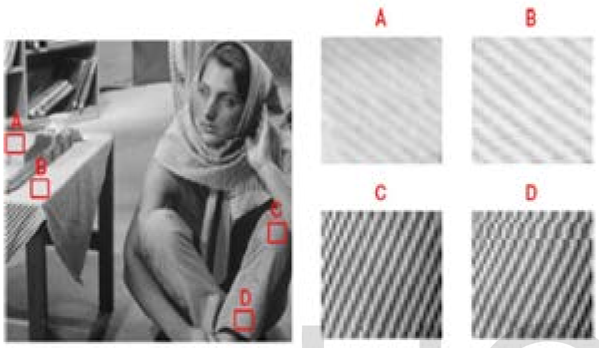

Fig. 1. (a) Babara image (b) similar structure blocks extracted from Barbara

The proposed approach of Prediction borrows its idea from motion prediction [5] Fig.2. In motion prediction Fig. 2, 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 proposed prediction approach Fig.3, 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.

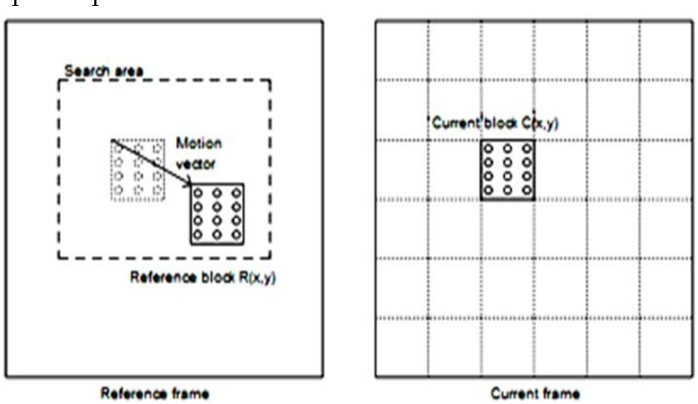

Fig.2. Motion Prediction in video coding.

We observe that the size of the prediction unit is an important parameter in spatial image prediction. For example, in pixel-level and block-based prediction, the prediction unit sizes are one pixel and one block, respectively. When the unit size is too small, the amount of prediction and coding overhead will be too 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

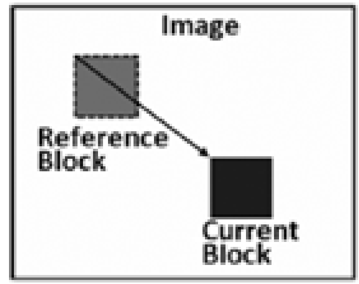

Fig.3. Proposed approach.

3.1 Block based image classification

The 512 x 512 grayscale image is partitioned into blocks of 4x4 blocks. Then the GAP (Gradient Adjusted Predictor) is performed on each block and prediction error is calculated. If the prediction error is greater than threshold then the block is consider as structure block otherwise nonstructure block. As per the result of GAP prediction, the block classification map (BCM) is maintained. Structure blocks are encoded using proposed approach of prediction whereas nonstructure blocks are encoded using conventional lossless image compression method, CALIC.

3.2 Structure block prediction

As the proposed approach of prediction is motivated from motion prediction in video coding, we used SAD (Sum of absolute difference) to compare current block with previously encoded structure blocks as shown in equation (1).

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

where $\mathrm{I}[i,j]$ is the pixel of the original block, and $\hat{\mathrm{I}}[\mathrm{i,j}]$ 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 structure block and its value is decided by experimenting different images and its compression results.

According to BCM, first block always taken as nonstructure block. Dynamic prediction approach starts from second block where it compares the current block with previous blocks. As our dynamic approach is designed to compare structure block with only previously encoded structure blocks, even if it founds nonstructure block it ignores and only performs the prediction with structure block and calculates SAD between current structure block and previously encoded all reference structure blocks.

3.3 Nonstructure block prediction using CALIC

CALIC(context based, adaptive lossless image codec) is a spatial prediction based scheme, in which GAP is used for adaptive image prediction [1] 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.This key feature of CALIC that distinguishes it from existing methods. CALIC only estimates expectation of prediction errors conditioned on a large number of contexts rather than estimating a large number of conditional error probabilities.

CALIC employs two step prediction/residual approach. In the prediction approach CALIC employs gradient based nonlinear prediction scheme, GAP (gradient adjusted predictor) which adjust prediction coefficient based on estimates of local gradients. Prediction is then made context sensitive and adaptive by modeling of prediction errors and feedback of expected error conditioned on properly chosen modeling contexts. The modeling context is a combination of quantized local gradient and texture pattern. 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 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) Prediction
2) Context selection and quantization
3) Context modeling of prediction errors
4) Entropy coding of prediction errors

4 PREDICTION RESIDUES ENCODING

Arithmetic coding [9], [10] is a form of entropy encoding used in lossless data compression, especially suitable for small alphabet (binary sources) with highly skewed probabilities. Arithmetic coding typically has a better compression ratio than Huffman coding, as it produces a single symbol rather than several separate codeword.

The idea behind arithmetic coding is to have a probability line, 0-1, and assign to every symbol a range in this line based on its probability. In this a unique identifier or tag is generated for the sequence to be encoded in order to distinguish a sequence of symbols from another sequence of symbols. This tag corresponds to a binary fraction, which becomes the binary code for the sequence. 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 we will use in developing the arithmetic code.

5 IMPLEMENTATION OF PROPOSED APPROACH

5.1) Encoder

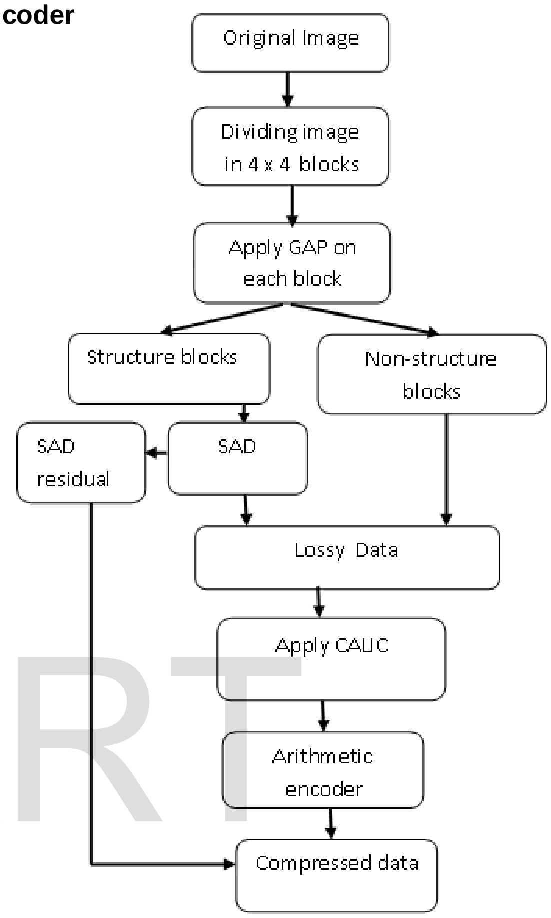

Fig.4. Proposed approach encoder

The original grayscale image of size 512 x512 is partitioned into 4 x 4 blocks.By applying GAP prediction on each block, the image is classified into structure and nonstructure blocks using threshold and maintained block classification map. Sum of absolute difference (SAD) of structure block is calculated to find repeatative structuere blocks by using SAD threshold and SAD residual factor is maintained. Nonstructure blocks are taken as it is. SAD satisfied structure blocks and nonstructure blocks are stored in lossy data.Then CALIC is applied on every single pixel of lossy data. Coding process is done with the help of arithmetic encoding. SAD residual and arithmetic encoder output forms compressed data.

5.2) Decoder

The compressed data received from encoder is separated as SAD residual and arithmetic encoded output. Arithmetic encoded output is given to decoderwhich gives lossy data. By using block classification map, structure blocks are repositioned using SAD residual and original lossless image is reconstructed.

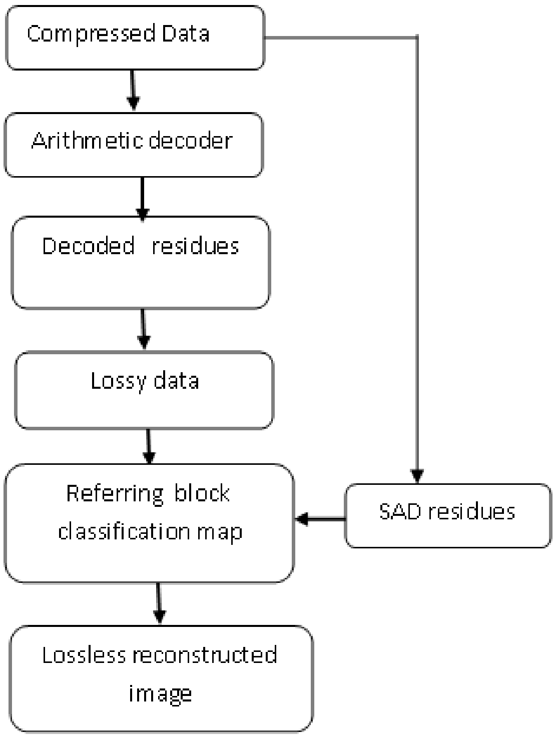

Fig.5. Proposed approach decoder

6 Simulation Results and Discussion

All the simulations were done using visual C++ on standard grayscale images like Lena, Barbara, Peppers, Mandrill having the size of 512x512pixels.

TABLE 1
COMPRESSION PERFORMANCE COMPARISON WITH CALIC

Image Name	Original size (Kb)	CALIC Compressed Size (Kb)	Proposed approach Compressed Size (Kb)	Compression ratio using CALIC	Compression ratio using proposed approach
Lena	257	135	108	1.9037: 1	2.3796 : 1
Barbara	257	152	112	1.6907	2.2946:1
Peppers	257	144	120	1.7847	2.1416:1
Mandrill	257	138	103	1.8623	2.4951:1

The compression performance comparison with CALIC [1] is tabulated in Table 1.
Comparative analysis of proposed approach and CALIC is done and result is obtained using compression ratio and bit rate parameters on different images with different structure and nonstructure regions.

From the graph as shown in fig.6, it is clear that Mandrill image have better compression ratio as compared to CALIC than other images,since it consist of more structure regions which can be successfully compressed by our approach of prediction

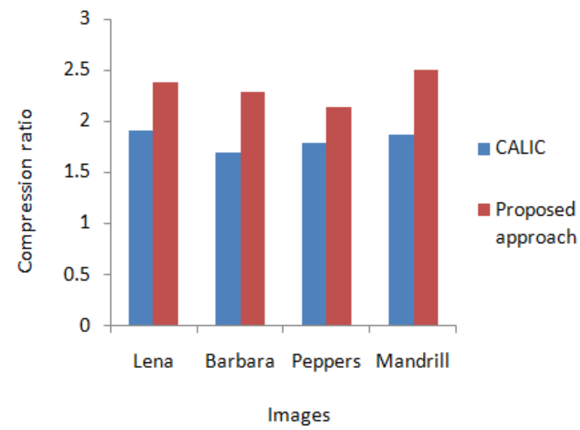

Fig.6. Comparison of Compression Ratio

In Table 2, we compare the coding bit rate of the proposed lossless image coding method based on proposed prediction approach with CALIC [1] and calculated bit rate saving.

TABLE 2
CODING BIT RATE COMPARISON WITH CALIC

Image Name	CALIC Bit Rate(bpp)	Proposed approach Bit Rate (bpp)	Bit Rate Saving
Lena	4.21	3.37	-0.84
Barbara	4.75	3.50	-1.25
Peppers	4.50	3.75	-0.75
Mandrill	4.31	3.21	-1.1

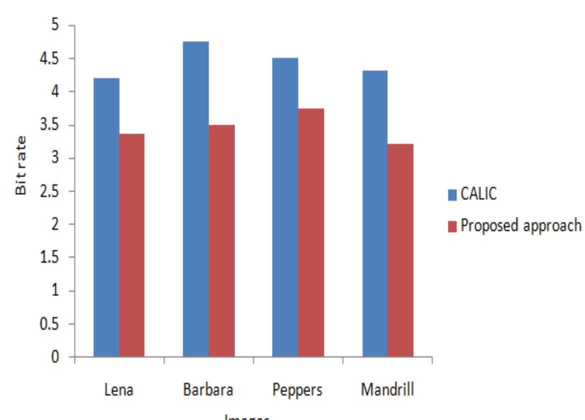

Fig.7. Comparison of Coding Bit-Rate

From the graph as shown in fig. 7 shows performance analysis of proposed approach with CALIC using bit rate parameter. In

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best case , original Mandrill image of 8 bits is compressed upto 3.21 bit rate as compared to CALIC having 4.31 bit rate.

7 Conclusion and Future Scope

In this approach we have developed efficient prediction scheme to compressed structural components from the image which is motivated by motion prediction in video coding, attempting to find an optimal prediction of a structure components within previously encoded image regions. By taking CALIC as the base code, the image was classified into various regions and they were encoded accordingly. The experimental results indicate that the proposed hybrid scheme using dynamic prediction approach is efficient in lossless image compression, especially for images with significant structure components.

This proposed approach of prediction is done using GAP in CALIC which can be further improved to avoid complexity and increases response time of proposed approach.

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References

[1] X. Wu and N. Memon, "Context-based, adaptive, lossless image coding," IEEE Trans. Commun., vol. 45, no. 4, pp. 437–444, Apr. 1997.

[2] M. J. Weinberger, G. Seroussi, and G. Sapiro, "The LOCO-I lossless image compression algorithm: Principles and standardization into JPEG-LS," IEEE Trans. Image Process., vol. 9, no. 8, pp. 1309–1324, Aug. 2000

[3] J. Ziv and A. Lempel, "A universal algorithm for sequential data compression," *IEEE Trans. Inform. Theory*, vol. 23, no. 3, pp. 337–343, May 1977.

[4] F.Wu and X. Sun, "Image compression by visual pattern vector quantization (VPVQ)," in *Proc. IEEE Data Compression Conf. (DCC'2008)*, pp. 123–131.

[5] T. Wiegand, G. J. Sullivan, G. Bjntegaard, and A. Luthra, "Overview of the H.264/AVC video coding standard," IEEE Trans. Circuits Syst. Video Technol., vol. 13, no. 7, Jun. 2003.

[6] B. Wohlberg and G. de Jager, "A review of the fractal image coding literature," IEEE Trans. Image Process., vol. 8, no. 12, pp. 1716–1729, Dec. 1999.

[7] Xiwen Zhao and Zhihai He," Local Structure Learning and Prediction for Efficient Lossless Image Compression", 2010 IEEE, pp. 1286-1289

[8] Xiwen OwenZhao, and Zhihai HenryHe," Lossless Image Compression Using Super-Spatial Structure Prediction", IEEE SIGNAL PROCESSING LETTERS, VOL. 17, NO. 4, APRIL 2010, pp. 383-386.

[9] David Salomon, "*Data Compression: A Complete Reference*", 3rd Edition, Springer, 2007.

[10] Khalid Sayood, "*Introduction to Data compression*", 3rd Edition, Elseiver Publications, 2006.