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Lossless Color Image Compression by Predictive Approaches: A Survey

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***Abstract*— There are numerous applications of image compression, such as the space imaging, medical imaging, classic and digital imaging where the size of images or image stream is too large and requires a large amount of space for storage or high bandwidth for communication purpose in its original form. The techniques lossless image compression preserves information so that from the compressed data exact reconstruction of image is possible. In the lossless color image compression the concern existing algorithms are broadly classified as the predictive approaches and the transform approaches. The predictive approach is one of the best methods for lossless image compression. A review on the various existing predictive approaches for lossless image compression is discussed here.**
***Keywords*— reversible color transform, lossless image compression, prediction, context modelling, entropy coding.**

I. INTRODUCTION

Recently it has seen that a level of research in image compression is increasing. Most of the efforts have given on the development of lossy compression techniques. In many applications require lossless image compression. Hence, an important research topic is the development of effective lossless image compression. RCT is used for reducing the correlation of channels of color images. The RCT followed by the grayscale lossless compression enhances the compression rate.

There are two types of approach for lossless image compression: transform based method and prediction based method. In case of transform base method Discrete Wavelet Transform (DWT) plays an important role. The DWT decomposes a given image in the different levels. These decomposition levels consist of a number of sub bands with coefficients that describe the vertical and horizontal spatial frequency characteristics of original image. In JPEG 2000 standard [1] in the form of dyadic decomposition only power of 2 decompositions are allowed. DWT can be reversible or irreversible. If the wavelet basis is float type, we must overcome the obstacles of the precision error and boundary error if we apply it in lossless transform directly. The results are of float type when image data of integer type is transformed. So for lossless image compression the conventional wavelet transforms are not suitable. The second generation lifting scheme [2] based integer wavelet transform can map integer to integer and reconstructed image quality is independent of extend type and boundary transform uses. Here the lifting scheme based techniques applied to lossless image compression are EZW algorithm [3], SPIHT algorithm [4] , EBCOT [5] , BWT [6], TDKZW [7] etc.

The following figure shows the general scheme for the lossless image compression and common scheme for leveling the casual pixels.

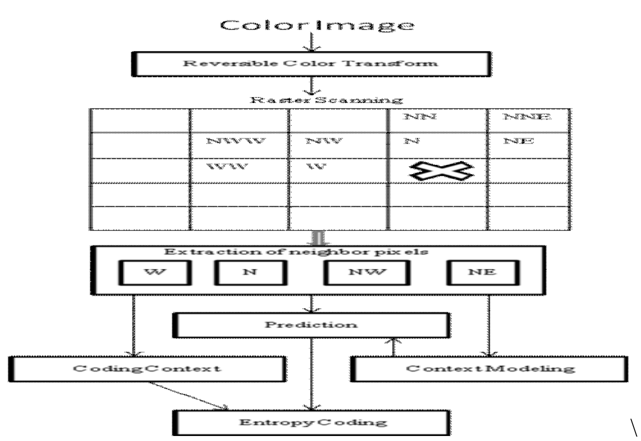

Fig.1.General scheme for lossless image compression

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The predictive approaches use a simple assumption that the pixel value can be totally or partially represented as a linear combination of neighbor pixels. For the transformed based techniques the data is transformed in such a way that allows better exploitation of spectral component which are present on the image. For lossless image compression, before transformation the prediction is chosen because it is fast, simple and the most important is that it can guarantee a lossless data recovery. The prediction based algorithm use the following three steps: a) the efficient and simple predictor that removes most of the existing redundancy. b) Secondly, the context modeling for further exploits the repeating pattern for improving the prediction. c) Lastly, the entropy coding for remove the statistical redundancy.

The paper can be divided in the following ways that: in section II represents reversible color transform. In section III describes some prediction techniques. And in section IV explain the context modeling. Section V represents the entropy encoding. Section VI shows the review of literature and at last in the section VII we share the conclusion of work.

II. REVERSIBLE COLOR TRANSFORM

Usually the natural color images are represented with three color values per pixel: red, green and blue. Before the compression a color transform is necessary for correlation of color channel significantly. As example, for the lossy compression, the YCbCr transform is used is defined as below:

$$\begin{pmatrix} Y \\ Cb \\ Cr \end{pmatrix} = \begin{pmatrix} 0.299 & 0.587 & 0.114 \\ -0.16875 & -0.33126 & 0.5 \\ 0.5 & -0.41869 & -0.08131 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$

But, this cannot be used for the lossless color image compression because it has no exact invertible transform with the integer arithmetic. In case of JPEG 2000, color transform which is reversible is introduced as below:

$$\begin{array}{lcl} Y = (R + 2G + B)/4 & & G = Y - (Cu + Cv)/4 \\ Cu = R - G & \leftrightarrow & R = Cu + G \\ Cv = B - G & \leftrightarrow & B = Cv + G \end{array}$$

Here the term "reversible" is used because the transform is exactly invertible with the integer arithmetic and is very simple.

III. SOME PREDICTION TECHNIQUES

The prediction is an important part of the lossless image compression. Spatial redundancy can be removed by it. For efficient compression, the choice of appropriate predictor is required. It may be linear or non-linear. It depends on the context region like smooth, texture, horizontal and vertical edge etc.

A. Lossless JPEG Predictors

The first version of the lossless JPEG, based on prediction, introduced seven simple predictors for spatial redundancy removal. W, N, NW, W+N-NW, (N+W)/2, W+ (N-NW)/2 and N+(W-NW)/2 are these predictors . After prediction, the error image is coded using entropy coder.

B. Median Edge detection Predictor

Median Edge Detection (MED) predictor was proposed by Martucci [8] and is used in JPEG-LS [9]. It belongs to the group of switching predictors that select one of optimal sub predictors depending on the smooth region [10], vertical edge and horizontal edge. Between the possibilities N, W and W+N-NW it selects the median value.

C. Gradient Adaptive Predictor (GAP)

GAP is employed in the context-based, adaptive, lossless image (CALIC) scheme [11]. CALIC encodes and decodes a given image symmetrically in the raster scan order. It predicts the current pixel by the local gradient information. The first step is to estimate the local horizontal and vertical gradient:

$$g_v = |W - WW| + |N - NW| + |N - NE|$$
$$g_h = |W - NW| + |N - NN| + |NE - NNE|$$

After that, prediction P is done according to this estimations:

$$\begin{aligned}
&\text{if } g_v - g_h > 80, P = W; \text{ elseif } g_v - g_h < -80, P = N;\\
&\text{else } P = (W + N) / 2 + (NE - NW) / 4;\\
&\text{if } g_v - g_h > 32, P = (P + W) / 2;\\
&\text{elseif } g_v - g_h > 8, P = (3P + W) / 4;\\
&\text{elseif } g_v - g_h < -32, P = (P + N) / 2;\\
&\text{elseif } g_v - g_h < -8, P = (3P + N) / 4;
\end{aligned}$$

D. SFALIC Predictor

A fast and simple lossless image compression is introduced by the authors in [12]. The main intension of the algorithm is high processing speed with high compression ratio. By using the three lossless JPEG predictors this proposed sub predictor is made as below:

$$P = (3A + 3B - 2C)/4$$

E. Gradient Edge Detection Predictor

It is proposed to be a tradeoff between the efficiency like GAP [13] and simplicity like MED. This predictor uses local gradient estimation like GAP. Between MED and GAP the number of the causal pixels is a compromise. The local gradient estimation is made with:

$$g_v = |NW-W|+|NN-N|$$
$$g_h = |WW-W| + |NW-N|$$

after that the prediction is occurred according to the following equation:

$$\begin{aligned}
&\text{if } g_v - g_h > T, P = W;\\
&\text{elseif } g_v - g_h < -T, P = N;\\
&\text{else } P = N + W - NW
\end{aligned}$$

where T is a threshold.

F. Least Absolute Deviation Predictor

Least Absolute Deviation (LAD) predictor adapts coefficients by minimizing the sum of absolute errors taken from casual set. One possible approach is the weighted iterative adaptation of coefficients [14]. This approach uses several least square adaptations and it is shows to converge linearly towards optimal LAD solution.

G. Hierarchical Prediction Techniques

Author in [15] proposed a new prediction techniques in which horizontal and vertical predictor are used which are defined as follows:

$$\hat{x}_h (j, k) = X_0 (j, k-1)$$
$$\hat{x}_V (j, k) = \text{round}\,[X_e (j+1, k) + X_e (j, k)]/2,$$

With the help of two predictors the most common approach to encoding is "mode selection", where for each pixel the selection of the better predictor is done and the mode also transmitted as side information. Here it is seen that than the horizontal predictor the vertical predictor is more correct because the upper and lower pixel are used for the "vertical" and just left pixel is used for the" horizontal". For a strong horizontal edge the horizontal predictor is more accurate.

IV. CONTEXT MODELING

For further improvement of prediction, the context modeling uses repetitive patterns of neighbor of the current pixel. Here contain textures are characterized with the neighboring pixels values. For each scheme the context modeling updating occurs for each time and learns the pixel value of probability distribution. For example, it is seen that there are 2^m possible schemes for m previous pixels in the binary images. The context is made with the group of similar scheme and prediction correction is crucial for avoiding that bottle neck. By using a detection rule a context is determined. The accumulator and the counter are updated for each context. For each time a context is detected a counter M is incremented and the accumulator B is a sum of prediction error. The correction of the predictive value is occurred after the prediction and context detection:

$$Pc = P + [B / M]$$

Here P is the prediction value.

A context dilution is a phenomenon when the number of contexts is high so during image scanning they cannot be learned. A smaller number of contexts are also not optimum, because the conditional probability may not determine an optimum correction for prediction. Image with different textures is another problem is areas. For every context by setting a limit of a counter these problems are usually solved.

V. ENTROPY CODING

In case of lossless image compression the entropy coding is one of the important steps where actual compression occurs.

To store an image, the variable length code word takes less memory space than the fixed length code word. There are a number of entropy coders among them the Huffman coder, Golomb-Rice coder and arithmetic coder [16]-[19] are the most popular.

The Huffman encoding is a coder of variable length and based on the statistical methods. Based on the probability of symbols occurring in a sequence, it forms a table. To compute probability of each symbol, the entire sequence is scanned and then the Huffman table is constructed.

The Golomb Rice Code is also a variable length code. It is based on a simple model. The precise relationship between the probability and size is captured in a parameter, the divisor which is used in JPEG-LS.

The Arithmetic coding is based on representing a sequence of events as an interval between the two numbers. It was designed for the arithmetic of floating-point. However, to use considerably faster integer arithmetic (CALIC and TMW used arithmetic coding) it can be modified.

VI. REVIEW OF LITERATURE

Marcelo J. Weinberger et al. in [20] described that the LOCO-I (Low Complexity Lossless Compression for Images) is the algorithm at the core of the new ISO/ITU standard for lossless and near-lossless compression of continuous-tone images, JPEG-LS. It is conceived as a "low complexity projection" of the universal context modelling paradigm, matching its modelling unit to a simple coding unit. By combining simplicity with the compression potential of context models, the algorithm "enjoys the best of both worlds." It is based on a simple fixed context model, which approaches the capability of the more complex universal techniques for capturing high-order dependencies. The model is tuned for efficient performance in conjunction with an extended family of Golomb-type codes, which are adaptively chosen, and an embedded alphabet extension for coding of low-entropy image regions. LOCO-I attains compression ratios similar or superior to those obtained with state-of-the-art schemes based on arithmetic coding. Moreover, it is within a few percentage points of the best available compression ratios, at a much lower complexity level. We discuss the principles underlying the design of LOCO-I, and its standardization into JPEG-LS.

X.Wu et al. in [21] described a context-based, adaptive, lossless image codec (CALIC). The codec obtains higher lossless compression of continuous-tone images than other lossless image coding techniques in the literature. This high coding efficiency is accomplished with relatively low time and space complexities. CALIC puts heavy emphasis on image data modeling. A unique feature of CALIC is the use of a large number of modelling contexts (states) to condition a nonlinear predictor and adapt the predictor to varying source statistics. The nonlinear predictor can correct itself via an error feedback mechanism by learning from its mistakes under a given context in the past. In this learning process, CALIC estimates only the expectation of prediction errors conditioned on a large number of different contexts rather than estimating a large number of conditional error probabilities. The former estimation technique can afford a large number of modelling contexts without suffering from the context dilution problem of insufficient counting statistics as in the latter approach, nor from excessive memory use. The low time and space complexities are also attributed to efficient techniques for forming and quantizing modelling contexts.

Seyun Kim et al. in [22] described that in many conventional lossless color image compression methods, the pixels or lines from each color component are interleaved, and then they are predicted and coded. Also, it has been reported that the reversible color transform (RCT) followed by a grayscale encoder gives higher coding gain than the independent compression of each channel does. In this paper, we propose a lossless color image compression method that concentrates on the efficient coding of chrominance channels with a new color transform and hierarchical coding of chrominance channel pixels. Specifically, we first transform an input image with R, G, and B color space into Y C_uC_v color space using the proposed RCT, which shows better de-correlation performance than the existing RCT. After the color transformation, the luminance channel Y is compressed by a conventional lossless image coder, such as JPEG-LS, CALIC, or JPEG2000 lossless. Unlike the luminance channel, the chrominance channels C_u and C_v are relatively smooth and have different statistical characteristic. Therefore, the chrominance channels are differently encoded based on a hierarchical decomposition and directional prediction. Finally, effective context modeling for prediction residuals is adopted. Experimental

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results show that the proposed method improves the compression performance by 40% over the conventional channel independent compression methods and 5% over the existing methods that exploit the channel correlation.

Yong Zhang et al. in [23] explained that Context-based modeling is an important step in high-performance lossless data compression. To effectively define and utilize contexts for natural images is, however, a difficult problem. This is primarily due to the huge number of contexts available in natural images, which typically results in higher modeling costs, leading to reduced compression efficiency. Motivated by the prediction by partial matching context model that has been very successful in text compression; it is presented prediction by partial approximate matching (PPAM), a method for compression and context modeling for images. Unlike the PPM modeling method that uses exact contexts, PPAM introduces the notion of approximate contexts. Thus, PPAM models the probability of the encoding symbol based on its previous contexts, whereby context occurrences are considered in an approximate manner. The proposed method has competitive compression performance when compared with other popular lossless image compression algorithms. It shows a particularly superior performance when compressing images that have common features, such as biomedical images.

Nikolaos V. Boulgouris et al. in [24] explained that the optimal predictors of a lifting scheme in the general n-dimensional case are obtained and applied for the lossless compression of still images using first quincunx sampling and then simple row–column sampling. In each case, the efficiency of the linear predictors is enhanced nonlinearly. Directional post-processing is used in the quincunx case, and adaptive-length post-processing in the row–column case. Both methods are seen to perform well. The resulting nonlinear interpolation schemes achieve extremely efficient image decorrelation. We further investigate context modeling and adaptive arithmetic coding of wavelet coefficients in a lossless compression framework. Special attention is given to the modeling contexts and the adaptation of the arithmetic coder to the actual data. Experimental evaluation shows that the best of the resulting coders produces better results than other known algorithms for multiresolution-based lossless image coding.

Stefano Andriani et al. in [25] presented a novel technique that uses the optimal linear prediction theory to exploit all the existing redundancies in a color video sequence for lossless compression purposes. The main idea is to introduce the spatial, the spectral, and the temporal correlations in the autocorrelation matrix estimate. In this way, we calculate the cross correlations between adjacent frames and adjacent color components to improve the prediction, i.e., reduce the prediction error energy. The residual image is then coded using a context-based Golomb–Rice coder, where the error modeling is provided by a quantized version of the local prediction error variance. Experimental results show that the proposed algorithm achieves good compression ratios and it is robust against the scene change problem.

VII. CONCLUSION

We have discussed here the various methods of predictive based lossless color image compression. Though, a number of predictive methods available there, the need for improved performance demands newer and better techniques. In the near future a better trade-off between the error block and the information which we send towards decoder can be explored.

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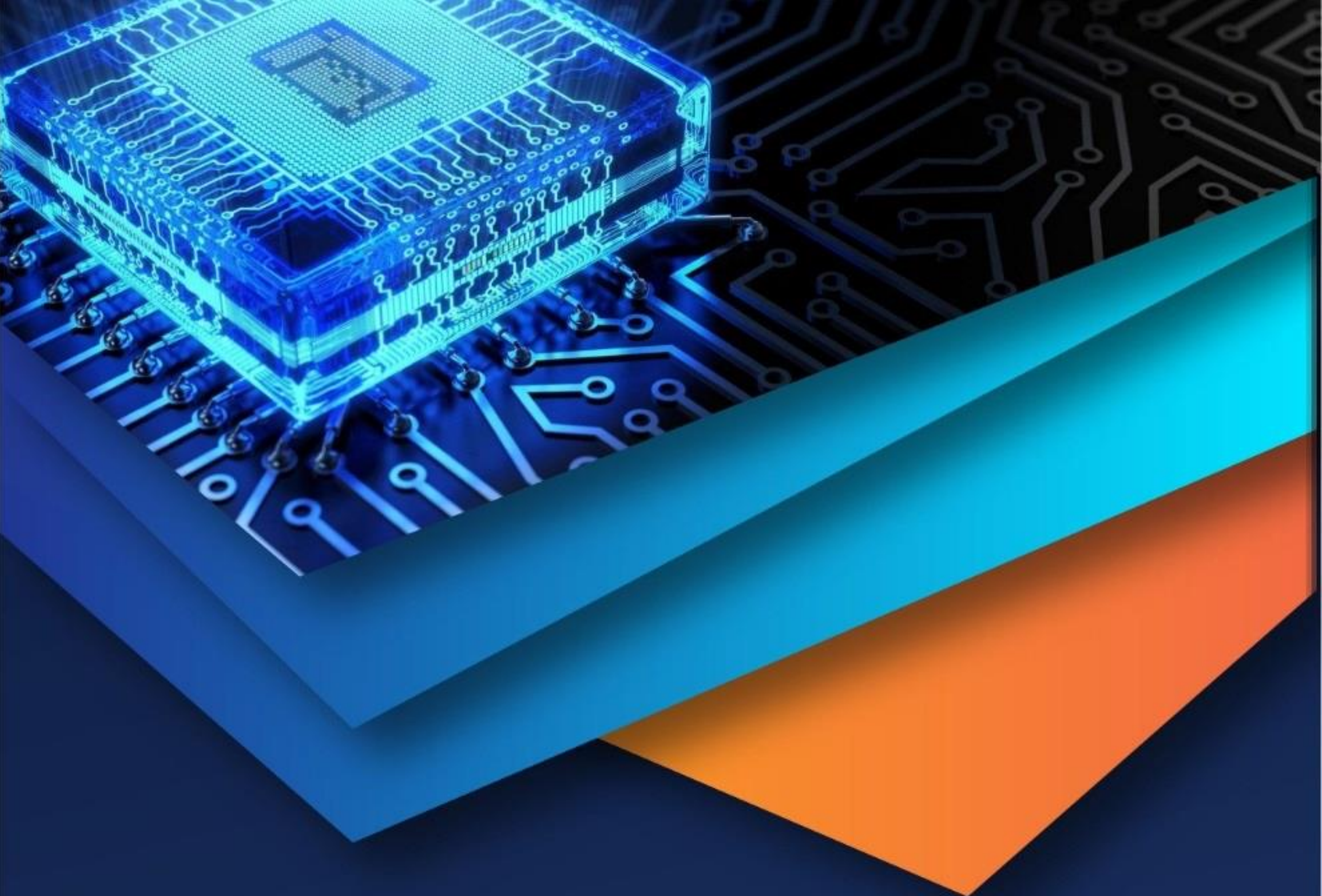

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