Gradient edge detection predictor for image lossless compression

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Abstract — **There are many examples of digital image processing where lossless image compression is necessarily, due to the costs of data acquisition or legal issues, such as aerial and medical imaging. Need for lossless compression of large amounts of data requires speed and efficiency, so predictive methods are chosen before transform-based methods. Predictive methods rely on prediction, context modeling and entropy coding. Predictor is the first and the most important step which removes a large amount of spatial redundancy. The most representative predictors are median edge detection (MED) predictor used in JPEG-LS standard and gradient adjusted predictor (GAP) used in CALIC. This paper presents a novel threshold controlled, gradient edge detection (GED) predictor which combines simplicity of MED and efficiency of GAP. Amount of removed redundancy is estimated with entropy after prediction. Analysis shows that GED gives comparable entropies with much complicated GAP.**

Keywords-component; data compression; images; prediction; entropy.

I. INTRODUCTION

Digital grayscale image is mostly represented as a two-dimensional integer matrix, where every matrix value represents appropriate pixel intensity. Color images are represented by at least three matrices, where every matrix matches one base color. Digital image compression can be lossless which preserves original image data and lossy which keeps only the data that carry most important information. More precise, lossless image compression converts data without loss of information, so less memory is required. Lossy image compression usually discards data that carry information that human visual system can't notice, so even less memory is required for storage. The most popular and widely used transform-based compression techniques, such as base JPEG standard, can not guarantee a lossless compression, due to the non-integer data transform, which introduces a round-off error. Besides, predictive methods are simple and fast, so they are often used when original data must be preserved. For example, medical image compression must be lossless due the legal issues, because diagnostic information must be preserved.

Predictive techniques for lossless compression rely on prediction, context modeling and entropy coding [1]. Prediction removes spatial redundancy, thus exploiting smooth areas in images. Context modeling further improves prediction by including information about pixels context, such as horizontal or vertical edges, texture etc. Entropy coding removes statistical redundancy forming a final code stream. In this paper, predictors are discussed and analyzed.

This paper discusses a novel predictor which is based on assumed simplicity and efficiency. Simplicity requires that predictor must be integer-based, because hardware implementation is faster and simpler. Efficiency requires that entropy of prediction error image is comparable with state of the art predictors.

Paper is organized as follows. In Section II basic concept of lossless image compression is described. Section III explains most referent predictors, MED and GAP with their advantages and drawbacks. Proposed GED predictor is presented in Section IV, while Section V gives a side by side analysis of described predictors. Section VI is a conclusion.

II. LOSSLESS IMAGE COMPRESSION

A. Compression Efficiency

Lossless image compression must preserve every pixel intensity value regardless whether it is a noise or not. Efficiency of compression codec is usually described by compression ratio. Compression ratio is ratio between memory space needed to store raw image and memory space needed to store compressed data, i.e. code stream. Equivalent measure is bit rate, which shows how many bits per pixel are required for an image in average. Another important measure, which is useful to estimate compression ratio, is called entropy. Entropy theoretically describes a minimum bit rate subject to the assumption that images are first order Markov processes. If we denote an image as a random variable X, with an alphabet $A = (a_0, a_1, a_{2...}\, a_{N-1})$, which mean we have an N-bit image, entropy can be calculated as follows:

$$H(X) = -\sum_{x \in A} p(x) \log_2 p(x), \tag{1}$$

where $p(x)$ is associated probability of a symbol x. Since this paper discusses a prediction, entropy will be used to estimate efficiency of prediction algorithms.

B. Lossless Compression Scheme

General lossless compression scheme consists of a predictor, context modeling block, coding context block and entropy coder (Fig. 1). Predictor predicts current pixel intensity from a finite number of causal pixels from raster scan order.

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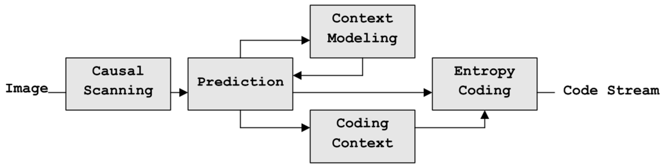

Figure 1. General predictive image lossles compression scheme.

Prediction output is a prediction error image *E*. The difference between the prediction and original intensity is coded, thus removing spatial redundancy. Context modeling block further improves prediction with feedback on usual texture blocks appearing on image. Context is estimated from causal pixels as well, and it exploits a fact that the conditional probability of prediction error image *p(E|Δ)*, where Δ is context condition, is less than original probability of prediction error image *p(E)*. Coding context block preprocesses data to ensure more efficient entropy coding. It can include alphabet reduction, prediction error remapping and conditional coding.

III. RELATED WORK

During the last twenty years many predictive methods were proposed with their advantages and drawbacks. We can separate two categories of most common used predictive methods. The first predictive method is based on static predictor which is usually a switching predictor able to adapt to several types of context, like horizontal edge, vertical edge or smooth area. For example, MED predictor [2] is used in LOCO-I lossless compression algorithm and in JPEG-LS standard. The second predictive method was introduced during the recent years and it is based on least mean square adaptation of linear predictive coefficients [4-6]. The adaptation is done from causal neighbor pixels, so every pixel intensity value could be predicted with an optimal predictor. Since least mean square adaptation is computationally expensive, many methods for look-ahead edge detection were proposed. It was noticed that coefficient adaptation is most necessary in edge and noise areas, so only when such an area is detected, adaptation is performed.

A. Predicion using Median Edge Detector

Median Edge Detector (MED) is a combination of simplicity and efficiency. MED uses only three causal pixels to determine a type of pixels area which is currently predicted. Predictor then decides whether the pixel is in horizontal edge, vertical edge or smooth area. We can classify MED as a switching predictor based on local characteristics. Based on the selected type of causal area, MED uses one of three possible sub predictors [2]:

$$P=\begin{cases}\min\left(A,B\right), if\ C\geq\max\left(A,B\right)\\ \max\left(A,B\right), if\ C\leq\min\left(A,B\right)\\ A+B-C, else\end{cases}. \qquad (2)$$

Causal neighbor pixels are shown in Fig. 2. Observing the (2) we can conclude that MED predictor chooses a median value between values *A*, *B* and *A*+*B*-*C*. Although the compression methods that use MED have a local gradient estimation, MED does not use them. The second drawback is a fact that MED can't adapt on high-noise areas.

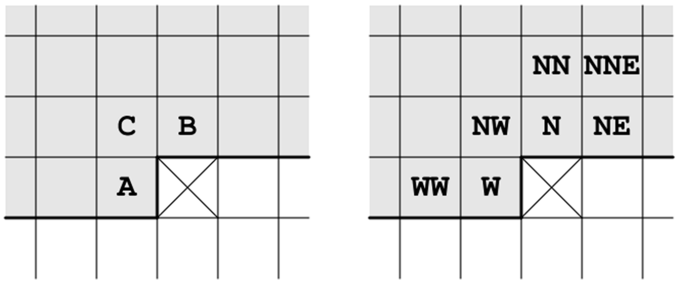

Figure 2. Causal pixels for MED predictor (left) and causal pixels for GAP predictor (right).

B. Prediction using Gradient Adjusted Predictor

Gradient Adjusted Predictor (GAP) [3] is embedded in CALIC algorithm, one of the representative linear prediction lossless image codecs. Most important advantage of the GAP predictor is high adaptability, because GAP recognizes weak, regular and sharp horizontal and vertical edges, as well as smooth areas. To detect edges, predictor uses local gradient estimation and three heuristic defined thresholds. Vertical and horizontal gradients are estimated as follows:

$$\begin{aligned} g_v &= \left|W-WW\right|+\left|N-NW\right|+\left|N-NE\right| \\ g_h &= \left|W-NW\right|+\left|N-NN\right|+\left|NE-NNE\right|. \end{aligned} \qquad (3)$$

Labels for causal neighbor pixels are marked on Fig. 2. A prediction is further made according to:

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

GAP achieves smaller error image entropy than MED, but it is far more complicated and uses three heuristic thresholds.

C. Prediction using Minimum Mean Square Error

Minimum Mean Square Error (MMSE) [7] predictor uses least mean square principle to adapt *k*-order linear predictor coefficients for optimal prediction of the current pixel, from a fixed number of *m* causal neighbors. If we denote last *m* prediction errors with a vector:

$$\mathbf{e}=\left[e_1,e_2,\ldots e_m\right]^T, \qquad (5)$$

last *m* observation pixels intensity values with:

$$\mathbf{y}=\left[y_1,y_2,\ldots y_m\right]^T \qquad (6)$$

and training causal pixel intensity values with

$$\mathbf{C}=\begin{bmatrix} y_{11}, & y_{12}, & \cdots & y_{1k} \\ \vdots & \vdots & & \vdots \\ y_{m1}, & y_{m2}, & \cdots & y_{mk} \end{bmatrix}, \tag{7}$$

then the optimal predictor coefficients matrix is found as a solution of:

$$\mathbf{e}=\left\|\mathbf{y}-\mathbf{Ca}\right\|_2 \tag{8}$$

where **a** is:

$$\mathbf{a}=\left[a_1,a_2,\ldots a_k\right]^T . \tag{9}$$

Solution of (8) can be expressed as:

$$\mathbf{a}=\left(\mathbf{C}^T\mathbf{C}\right)^{-1}\left(\mathbf{C}^T\mathbf{y}\right). \tag{10}$$

Calculating a matrix of optimal coefficient **a**, from (10), for every pixel, could be heavily computational demanded, especially for a large size images. Therefore, there were a several proposals for reducing computational activity for edge area pixels, as in [5-6].

IV. Proposed Solution

Proposed solution is based on presumptions discussed in Introduction, so MMSE approach was avoided. Proposed Gradient Edge Detection (GED) predictor tends to use advantages of described MED and GAP predictors. MED is very simple and efficient predictor that recognizes three different types of causal areas. GAP uses gradient estimation and thresholds for prediction. Combining these two characteristics, GED is designed.

A. Prediction using Gradient Edge Detection Predictor

GED uses five causal neighbor pixels to estimate local gradient and to predict current pixel intensity value, which is a compromise between MEDs three and GAPs seven neighbor pixels. Similarly to GAP, local gradient is estimated, but unlike GAP, proposed solution uses only one threshold, which can be user defined. Local gradient is estimated as follows:

$$g_v=\left|C-A\right|+\left|E-B\right|$$
$$g_h=\left|D-A\right|+\left|C-B\right| . \tag{11}$$

Labels for causal neighbor pixels are marked on Fig. 3. Similarly to GAP, a prediction is further made according to:

$$\begin{aligned}&\mathit{if}\ g_v-g_h>T, P=A\\ &\mathit{elseif}\ g_v-g_h<-T, P=B\\ &\mathit{else}\ P=3\left(A+B\right)/8+\left(C+D+E\right)/12 .\end{aligned} \tag{12}$$

where T is a predefined threshold.

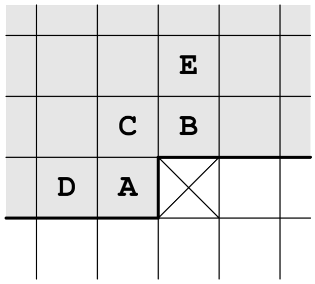

Figure 3. Causal pixels for GED predictor.

As we can see, GED algorithm is very simple, it chooses between, vertical edge, horizontal edge or smooth area like MED predictor, but mechanism for prediction is based on GAP predictor. GED estimates local gradient and uses one threshold for prediction. Threshold can be predefined and fixed, or user defined for every image.

V. Compare Analysis

To estimate efficiency of proposed algorithm, compared to reference predictors, entropy was calculated on prediction error images. For compare analysis a group of usual test images were used. According to the Shannon's noiseless coding theorem, entropy estimates a minimum bit rate for lossless compression using an entropy coding technique. Prediction is a simple tool for removing a spatial redundancy, thus reducing final bit rate after entropy coding.

We compare GED in relation to the MED and GAP, because MMSE predictor doesn't satisfy a simplicity principle. Entropies after prediction for MED, GAP and GED with threshold equals 8, is given in Table I. Examples of the test images are shown in Fig. 4.

Figure 4. Examples of test images, from left to right an from top to bottom: *cameraman, lena, peppers, lake, plane, baboon, couple, lax* and *milkdrop*.

TABLE I. ENTROPIES OF PREDICTION ERROR IMAGES FOR MED, GAP AND GED (WITH THRESHOLD 8) PREDICTORS.

Image	Entropies after prediction [bpp]		
	MED	***GAP***	***GED8***
cameraman	4.74	4.72	4.68
lena	4.54	**4.39**	4.54
peppers	4.93	**4.72**	4.81
boats	4.30	**4.28**	**4.28**
goldhill	4.71	**4.67**	4.73
lake	5.38	**5.26**	5.37
plane	4.20	**4.15**	4.23
baboon	6.92	6.81	6.88
couple	**4.81**	4.82	**4.81**
lax	5.98	**5.87**	5.92
milkdrop	3.80	**3.76**	3.77
zelda	4.20	**4.04**	4.17
averaged	**4.88**	**4.79**	**4.84**

As expected GED gives a compromising bit rate between MED and GAP, but with fixed and not optimized threshold. Comparing with GAP, GED gives about 1% higher bit rates, but it is considerably simpler. Interesting practical example of lossless image compression is medical image compression. Although, there is often possible to segment region of diagnostic interest, usually there are legal restrictions to compress medical images with losses. Medical images often have different bit depth than 8 bpp, usually 12 or 16 bpp, therefore authors in [3] developed an adaptive scaling factor for local gradient estimates in GAP. Scaling factor, used in current scanning row, is based on cumulative error from previous row. If an image has a intensity resolution R, scaling factor is calculated according:

$$\lambda = 2^{-\left\lfloor \frac{R-8}{2} \right\rfloor - \max\left(0, \left\lceil \log_2 \sigma - 5 \right\rceil\right)} \qquad (13)$$

where σ is an average of error magnitudes in previous row.

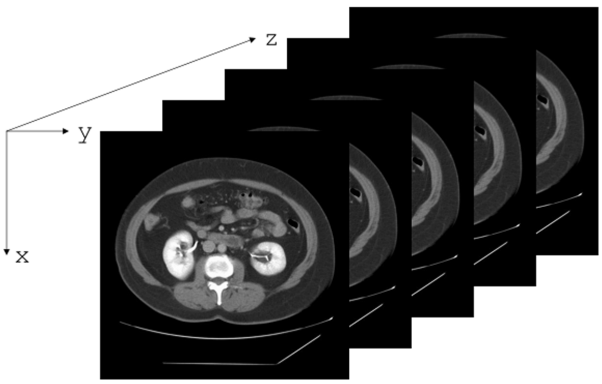

Figure 5. 3D CT image.

Table II gives results of prediction of three-dimensional 12-bit Computed Tomography (CT) and Magnet Resonance (MR) images. Prediction was done slice by slice and averaged entropy was calculated. Regular GAP, scaled GAP and GED predictors were used. An example of 3D CT image is given on a Fig 5.

TABLE II. AVERAGED ENTROPIES OF PREDICTION ERROR IMAGES FOR 12-BIT 3D CT AND MRI IMAGES, USING REGULAR GAP, SCALED GAP AND GED PREDICTORS.

Image	Image Size	Entropies after prediction [bpp]		
		GAP	***Scaled GAP***	***GED (Threshold)***
CT1	512x512x38	7.55	7.50	**7.44** (128)
MRI1	640x576x25	**4.85**	4.97	5.06 (16)
MRI2	320x288x25	**6.67**	6.73	6.76 (16)

From Table II, we can notice that computationally expensive scaling does not guarantee less entropy. It is also notable that with optimum threshold selection simple GED predictor can achieve comparable bit rates as more complicated GAP predictor.

VI. CONCLUSION

A novel simple predictor for lossless image compression is presented. Gradient Edge Detection predictor combines advantages of described GAP and MED predictors. Comparison between mentioned predictors showed that simple GED predictor can achieve comparable bit rate and that GED can be easily used for higher resolution images by selecting proper threshold.

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REFERENCES

[1] D. Salomon, Data Compression: The Complete Reference, Springer 2007.

[2] M. Wienberger, G. Seroussi, G. Sapiro, “LOCO-I: A Low Complexity, Context-Based, Lossless Image Compression Algorithm”, Proceedings of the Conference on Data Compression, p.140, March 31-April 03, 1996.

[3] X. Wu, N. Memon, “CALIC – A Context Based Adaptive Lossless Image Codec”, Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing ICASSP-96, vol. IV, pp. 1890-1893, May 1996.

[4] H. Ye, G. Deng, J. C. Devlin, “Least Squares Approach for Lossless Image Coding”, IEEE Int. Conf. Image Processing, pp. 901–904, 1998.

[5] X. Li, M. T. Orchard, “Edge-Directed Prediction for Lossless Compression of Natural Images”, IEEE Transactions on Image Processing, vol. 10, no. 6, pp. 813-817, 2001.

[6] H. Ye, G. Deng, J. C. Devlin, “A Weighted Least Squares Method for Adaptive Prediction in Lossless Image Compression” 23rd Picture Coding Symposium, 2003.

[7] F. Hsieh, K. Fan, “A High Performance Lossless Image Coder”, IPPR Conf. on Computer Vision & Graphic Image Processing 2005.