Symmetrical Predictor Structure based Integrated Lossy, Near Lossless/Lossless Coding of Images

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***Abstract*—Prediction based algorithms reported in the literature are not able to integrate lossy and near-lossless/lossless coding and uses only causal pixels (non-symmetrical predictor structure) for prediction. A non-symmetrical predictor structure, however, is not able to efficiently adapt near the intensity varying areas, which results into poor prediction. Hence, we propose a novel two-stage algorithm for lossy, near lossless/lossless compression using a symmetrical predictor structure is proposed. In the first stage, the proposed algorithm encodes and decodes the given image using the JPEG-2000 standard algorithm (lossy coding). This JPEG-2000 decoded image in the first stage, enables us to use the symmetrical predictor (using both causal and non-causal pixels) for prediction in the second stage. A performance evaluation shows that our algorithm is significantly better in terms of compression performance as compared to some of the computationally complex methods.**

***Index Terms*—Near-lossless and Lossless Image Compression, Symmetrical Predictor Structure, Computational Complexity.**

I. Introduction

Compression of picture signals is very important for transmission over communication channels and for storage purposes. Compression techniques can be divided into two categories: lossy and lossless compression. In some application areas exact replica of the original data, due to lossless compression is preferred over high compression ratio obtained with lossy methods. In order to achieve the trade-off between the compression ratio and distortion, near-lossless compression algorithms, in which a precise bound can be set on the distortion are proposed in literature. Some of the important application areas of lossless image compression are medical imaging, image archiving system, exact image analysis, remote sensing, GIS and cultural-heritage etc.

The state-of-the-art prediction based lossless image compression algorithms, include CALIC [1] and JPEG-LS [2]. These methods use switched predictors, namely Gradient Adaptive Prediction (GAP) [1] and Median Edge Detector (MED) [2], respectively. These methods are preferred because of their computational simplicity, but these methods are not able to perform well on the intensity varying areas (e.g, edges, patterns and texture). In order to solve this problem, Edge Directed Prediction (EDP) [5] and Run-length and Adaptive Linear Predictive (RALP) [6] algorithms are proposed in which least square (LS) based optimization is applied only on the detected edge pixels. On the same lines, Tiwari and Kumar [7] proposed an algorithm based upon the LS based optimization for pixel belongings to same slope bins of GAP [1]. Zhao [8] proposed a super spatial structure prediction (SSP) algorithm which merges CALIC [1] and intra-frame motion compensation. Unfortunately, the SSP [8] algorithm is not able to perform well when intra-frame redundancy is missing. Lee [9] uses control technologies to improve the predictive coding efficiency. Vinit [10] use interpolation based symmetrical predictor structure (ISPS) for better information exploitation from the neighboring pixels.

Most of the above described algorithms are not able to use a symmetrical predictor structure for prediction and arenot able to embed lossy and near-lossless/lossless compression. Hence, in order to overcome these problems, we proposed an efficient two stage near-lossless/lossless compression algorithm, which has the following advantages :

1) Our proposed algorithm efficiently integrates lossy and near-lossless/lossless compression.
2) Since the performance of the predictor depends on the predictor structure, we propose a symmetrical predictor structure to achieve better prediction accuracy as compared to existing unsymmetrical predictor structures.
3) As encoder of the proposed algorithm is require to optimize only 8 least-squares based predictors and the decoder does not require performance of any optimization,the encoder of proposed algorithm is computationally simple, while the decoder is even simpler.

The organization of the rest of this paper is as follows. In Sections II and III, the encoder and decoder of the proposed algorithm are discussed respectively. Section IV describes the trade-off between lossy and lossless compression bit-rates. The implementation results and comparison are provided in Section V. The conclusions are presented in Section VI.

II. Proposed algorithm

In this paper, we propose a new two stage integrated lossy and near-lossless/lossless image compression algorithm based on the symmetrical predictor structure. The existing prediction methods reported in [1]-[9], use only causal pixels

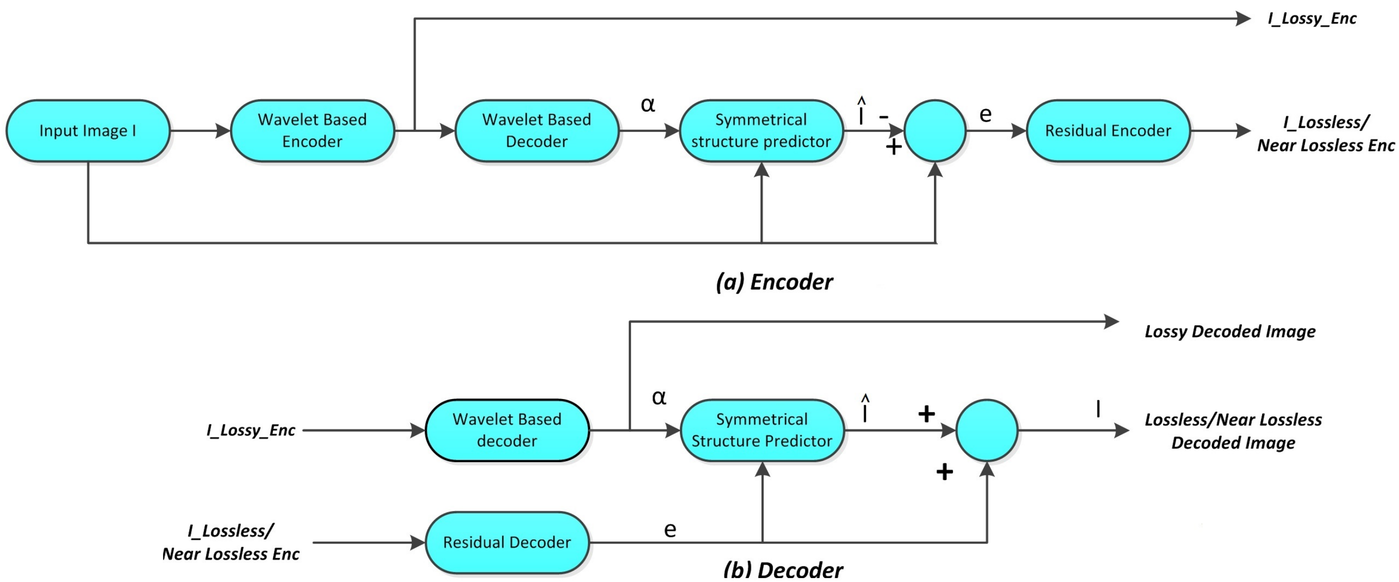

Fig. 1. Block diagram of proposed algorithm.

(non-symmetrical predictor structure) for prediction. This non-symmetrical predictor structure is not able to exploit the complete information from the neighboring pixels and is also not able to efficiently adapt near the intensity varying areas (e.g edges, patterns, textures etc.), which results into poor prediction and high residual energy.

To overcome the above described problems, a symmetrical structure and JPEG-2000 based two stage compression algorithm is proposed. In the first stage, the proposed algorithm encodes and decodes the given image with the help of the standard JPEG-2000 algorithm (lossy-algorithm), as shown in Fig. 1. These decoded pixels using the lossy JPEG-2000 algorithm are not precise but contain the much information about the non-causal pixels. Hence, these decoded lossy image pixels in the first stage enables the proposed algorithm to use the symmetrical predictor structure for prediction (using both causal and non-causal pixels). Through-out the paper, we define I, $\hat{I}$, $\tilde{I}$ and α as original image, predicted image using the symmetrical predictor, reconstructed image and lossy decoded image respectively. Details of the proposed symmetrical predictor structure are given in following subsections.

A. Integration of lossy and near-lossless/lossless compression and Symmetrical Predictor Structure

Pixels decoded in the first stage enables the proposed algorithm to use symmetrical predictor structure for predictions, as shown in Fig. 2. To encode this image, we estimate intensity the value variations (slope variation), at each pixel using both causal and non-causal neighboring pixels, in the directions of 45^0 and 135^0 and denote the same by d_{45} and d_{135} respectively, as shown in Fig. 2.

$$S = d_{45} - d_{135} \tag{1}$$

where d_{45} and d_{135} are obtained as follows:

$$\begin{aligned} d_{45} &= |I(n-1) - \alpha(n+2)| + |I(n-4) - \alpha(n)| \\ &\quad + |\alpha(n) - \alpha(n+4)| + |I(n-2) - \alpha(n+1)| \end{aligned} \tag{2}$$

$$\begin{aligned} d_{45} &= |I(n-1) - I(n-2)| + |I(n-3) - \alpha(n)| \\ &\quad + |\alpha(n) - \alpha(n+3)| + |\alpha(n+1) - \alpha(n+2)| \end{aligned} \tag{3}$$

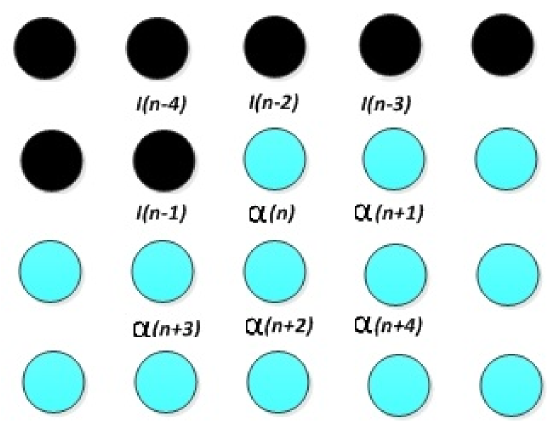

Fig. 2. Symmetrical predictor structure used for prediction. Here black and cyan circles represents causal pixels and lossy decoded non-causal pixels respectively.

Depending upon the slope variation S, all the pixels are classified into 8 bins, as shown in Table I. As, all the pixels are classified into 8 bins in such a way that the pixels in each bin shows same statistical characteristics (slope variation, edge direction, etc.) and alleviate the outliers and instability of the least squares estimation [4], it is prompt to estimate the least squared based optimized parameters for each bin, instead

TABLE I
CLASSIFICATION OF SLOPE BINS.

Input S	Bin	Description
$S \geq 40$	Bin 1	Sharp edge along angle 135
$40 \geq S \geq 20$	Bin 2	Edge along 135
$20 \geq S \geq 8$	Bin 3	Weak edge along angle 135
$8 \geq S \geq 0$	Bin 4	No edge
$0 \geq S \geq -8$	Bin 5	No edge
$-8 \geq S \geq -20$	Bin 6	Weak Edge along 45
$-20 \geq S \geq -40$	Bin 7	edge along angle 45
$S \geq -40$	Bin 8	Sharp edge along angle 45

of pixel by pixel optimization [5]-[6]. Proposed algorithm estimates least squared based parameters using kernel ridge regression (KRR) for each Bin i (where $i \in (1,2,...8)$).The linear predictor for Bin i is defined as :

$$f(x,w) = \vec{W}^T\vec{\phi}(x) = \sum_{k=1}^{9} W_k\phi_k(x) \tag{4}$$

where $\vec{W}$ is the 9-dimensional weight vector and $\vec{\phi}(x) = (\phi_1, ..., \phi_9) \in \mathrm{R}^{9\times 1}$ is the basis function vector containing the neighboring 9 pixels (both causal and non-causal pixels) in a 3×3 window, as shown in Fig. 2. In our algorithm, we estimated the least squared formulated optimized parameter for Bin i by minimizing the following Kernel ridge regression (cost function):

$$J(\vec{W}) = \sum_{k=1}^{M(i)} (x_k - \vec{W}^T\vec{\phi}(x_k))^2 + \lambda||\vec{W}||^2 \tag{5}$$

Here $x_k \in \mathrm{Bin}\,(i)$ and $M(i)$ is the total no. of pixels in Bin (i). In (5), $\lambda \geq 0$ is a parameter controlling the regularization, which enforces that the regression coefficients ($\vec{W}$) are close to zero and each other. This prevents the large, mutually canceling coefficients that can arise in normal (non-regularized) regression. As suggested in [4], optimal λ can be chosen from (0,1). Hence in our experiments, λ has chose to be as 0.5.

$$\vec{W}^* = \underset{W}{min} \quad J(\vec{W}) \tag{6}$$

Kernel Ridge regression (5) (KRR) is a convex problem without explicit constraint. Hence, we obtain the optimal weights $\vec{W}$ by differentiating (5) and equating to zero. So, the optimal solution of KRR in closed form is

$$\vec{W}^* = (\vec{\Phi}^T\vec{\Phi} + \lambda I)^{-1}\vec{\Phi}^T\vec{y} \tag{7}$$

Here I, is the identity matrix, $\vec{\Phi}(x)$=$[\vec{\phi}_1\ \vec{\phi}_2\ \vec{\phi}_k\ \ldots\ \vec{\phi}_{M(i)}]^T$ and $\vec{y}$=$[\vec{x}_1\ \vec{x}_2\ \vec{x}_k\ \ldots\ \vec{x}_{M(i)}]^T$. After estimating the KRR based parameters, these parameters are used to predict the pixels of the corresponding Bin i by the weighted sum of the neighboring 9 pixels (both causal and non-causal pixels) in a 3×3 window, as shown in (8).

$$\begin{aligned} \hat{I}\,(n) \quad &= w_1 I\,(n-1) + w_2 I\,(n-2) + w_3 I\,(n-3) \\ &+ w_4 I\,(n-4) + w_5\alpha\,(n) + w_6\alpha\,(n+1) \\ &+ w_7\alpha\,(n+2) + w_8\alpha\,(n+3) + w_9\alpha\,(n+4) \end{aligned} \tag{8}$$

Hence, in order to predict the entire image, our proposed algorithm requires to estimate only 8 least square based parameters of the 9^{th} order. These least squares based parameters for each bin are quantized with eight bits and sent to the decoder with the JPEG-2000 encoded image and residual image. The residual image (e) is defined as :

$$e = I - \hat{I} \tag{9}$$

Our proposed algorithm can be easily extended to near-lossless compression by quantizing the residual image (e) as :-

$$\hat{e} = \begin{cases} \left\lfloor \frac{e+\delta}{2\delta+1} \right\rfloor & e \geq 0 \\ \left\lfloor \frac{e-\delta}{2\delta+1} \right\rfloor & e < 0 \end{cases} \tag{10}$$

Here, $\lfloor . \rfloor$ is the floor function and δ is the maximum allowed distortion. The prediction residue (e) is uniformly quantized to $(\hat{e})$ by (10) to ensure that $||I - \tilde{I}||_\infty \leq \delta$. Here $\tilde{I}$ is the reconstructed value as $\tilde{I}$= $\hat{I}$ + $(2\delta + 1)\hat{e}$. In near-lossless compression, reconstructed pixels are used for prediction and encoding of the future pixels, in contrast to lossless compression in which the original pixels can be used.

III. DECODER OF PROPOSED ALGORITHM

At the decoder side we have residual image (e)/quantized residual image $(\hat{e})$, lossy encoded image and 8 LS based prediction parameters of 9^{th} order tagged with residual image. Our proposed algorithm reconstruct the image as follows :

1) First, our proposed algorithm decodes the lossy encoded image.
2) Next, our proposed algorithm formulates the symmetrical predictor structure for each pixel with the help of the already decoded causal pixels and lossy decoded image (non-causal pixels).
3) From this symmetrical predictor structure, the activity level S is calculated as shown in (1) and depending upon the value of S, the corresponding 9^{th} ordered parameters are used for reconstruction of the pixels.
4) Steps 2 and 3 are repeated until all the pixels in the entire image are reconstructed.

As, it can be easily observed that the proposed algorithm does not require to optimize any parameters at the decoder side, the decoder is even more simple than the encoder.

IV. TRADE-OFF BETWEEN LOSSY AND OVERALL BIT-RATE

Our proposed algorithm requires sending of JPEG-2000 encoded image with the residual image and prediction parameters. The higher bit rate of the lossy encoded image increases the precision of the non-causal pixels, which results into the better prediction and a reduction of the entropy of the residual image, while, for the low bit rate of lossy encoded image, the non-causal pixels are not accurate, which turns into the higher entropy of the residual image. Hence, there is a trade-off between the bit rate of the lossy encoded image and the residual image. From extensive experiments on 49 standard test images [12], we found that 0.5 bit rate of the lossy encoded

TABLE II
SIMULATIONS RESULTS OF PROPOSED LOSSLESS ALGORITHM IN TERMS OF FIRST ORDER ENTROPY

Image	MED	GAP	[7]	EDP	ISPS	SSP	Prop.
Lena	4.56	4.42	4.36	4.32	4.28	4.40	**4.21**
Home	6.38	6.50	6.36	6.35	6.29	6.42	**6.24**
Birds	4.14	4.05	4.03	4.06	4.07	4.02	**3.97**
Butterfly	5.04	5.11	5.02	4.99	4.94	5.06	**4.89**
Boat	4.62	4.59	4.50	4.47	4.52	4.54	**4.41**
Man	5.15	5.23	5.14	5.11	5.16	5.12	**5.03**
Seaview	**5.60**	5.78	5.72	5.73	5.7	5.71	5.62
Average	5.07	5.10	5.02	5.00	5.01	5.04	**4.91**

TABLE III
COMPRESSION COMPARISON OF PROPOSED LOSSLESS SCHEME IN TERMS OF BITS PER PIXEL (BPP)

Image	$JPEG-LS$[2]	$CALIC$[1]	SSP [8]	Proposed
Lena	4.24	4.11	4.09	**3.99**
Home	6.35	6.17	6.12	**6.00**
Birds	3.38	3.14	3.12	**3.03**
Butterfly	4.78	4.54	4.48	**4.37**
Boat	4.26	4.12	4.10	**4.01**
Man	4.94	4.80	4.72	**4.70**
Seaview	5.37	5.23	5.22	**5.12**
Average	4.75	4.59	4.55	**4.46**

image gives the minimum total bit rate (bit rate of the lossy encoded image and residual image), as shown in Fig. 3.

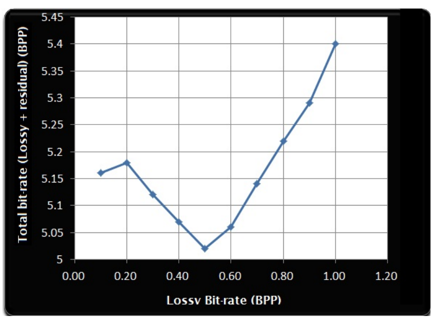

Fig. 3. Trade of between lossy and overall bit-rate for 49 standard [12] test image

V. SIMULATION RESULTS

The proposed symmetrical predictor structure based integrated lossy, near-lossless/lossless coding algorithm is implemented, and its performance for lossless coding is compared with the existing MED, GAP, EDP [5], super-spatial structure prediction (SSP) [8] and ISPS [10] algorithms. From Table II it can be observed that the proposed algorithm has very good prediction capability and achieves minimum first order entropy. We have made a complete lossless image coder and compared it with the JPEG LS [2], CALIC [1] and SSP [8] algorithms. Ad-hoc context modeling has been used for predicted error image. Bias cancellation methods have been used from CALIC.

As, some of the these algorithms do not exists in near-lossless mode (e.g EDP, GAP_{LS}, SSP), for near-lossless coding, our proposed algorithm is compared with JPEG-LS [2], CALIC [1], Ref [3] and Ref [11]. From Table IV, it can be concluded that the proposed algorithm has comparable performance.

TABLE IV
COMPRESSION COMPARISON OF PROPOSED NEAR-LOSSLESS SCHEME FOR LENA IMAGE IN TERMS OF BITS PER PIXEL (BPP)

	M=0		M=1		M=2	
Method	BPP	PSNR	BPP	PSNR	BPP	PSNR
JPEG-LS	4.24	∞	2.72	49.90	2.09	45.15
CALIC	4.11	∞	2.59	49.89	1.95	45.16
REF [3]	4.30	∞	2.77	49.89	2.12	45.17
REF [11]	4.49	∞	3.16	49.00	2.81	43.91
Proposed	**3.99**	∞	**2.47**	49.90	**1.89**	45.15

VI. CONCLUSIONS

In this paper, we propose a novel two-stage symmetrical predictor structure based integrated lossy, near-lossless/lossless image coding algorithm. Our proposed algorithm use non-causal pixels with causal pixels for prediction, and it is able to efficiently adapt near the intensity varying areas (edges, textures, patterns) and able to do better prediction. In future, we will try to use these available non-causal pixels for context modeling and bias cancellation (symmetrical bias cancellation). From the performance evaluation, we found that our algorithm is significantly better in terms of compression performance as compared to some of the computationally complex methods.

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