NEAR LOSSLESS IMAGE COMPRESSION BY LOCAL PACKING OF HISTOGRAM

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ABSTRACT

In this paper a low complexity algorithm is proposed for near lossless compression of images. The reconstructed near lossless image can differ from the original one within a pixelwise error tolerance. This property is used to convert the histogram of the original image, by the proposed algorithm, to a new histogram which is proved to have minimum entropy. Hence, a new image is formed which has minimum entropy and high spatial correlation among its pixels and can efficiently be compressed. Simulation results show the effectiveness of this compression algorithm.

Index Terms— near lossless compression, lossless compression, image histogram

1. INTRODUCTION

With evermore increase in transmission of images over mobile communication devices and internet importance of image compression is becoming more apparent. Many coding techniques have emerged with varying degrees of efficiencies. All these techniques can be basically classified into two main categories of lossy and lossless compression techniques. Lossy schemes discard the less relevant parts of the visual information of an image. This is the case, for example, of digital photography, where losing some of the image detail is tolerable. In lossless methods at the expense of lower compression ratios all of the original image information is maintained. Applications such as medical and space imaging or in remote sensing lossless compression is usually applied [1].

In many situations the exact lossless recovery is not essential deviation from original pixel values can be tolerated within certain error range. This error should not be averaged out through out the whole image, but rather for every pixel an error tolerance should be observed [2]. This pixelwise error tolerance gives rise a third type image compression known as *near lossless* scheme. Near lossless could significantly increase compression ratios while the reconstructed image pixels are guaranteed to have a maximum error within a tolerable range [3].

Near lossless approaches can be categorized into two groups: predictive coding based schemes [1, 4, 5, 6] and transform based methods [3, 7]. In [1] a DPCM coding scheme is employed incorporating entropy-minimization of the quantized prediction errors. In [4] an algorithm called CALIC (context-based, adaptive lossless-image codec) is proposed which performs error-constrained compression. JPEG-LS [5], is based on the LOCO-I algorithm developed at HP Labs and has low computational complexity and memory requirements. It also uses context-based entropy coding of the quantized prediction residuals. In [6], we proposed a trellis-based algorithm to perform a near lossless image compression.

In [3], the authors proposed a two stage near lossless compression scheme consisting of a wavelet-based lossy layer followed by a second stage for arithmetic coding of the quantized residuals. Also a wavelet-based two-stage near lossless coder is presented in [7]. It requires iterations to find the optimal first-stage bit rate and uses context-based entropy coding for residuals in the second stage.

Reference [6] uses a trellis-based non-iterative algorithm to obtain maximum run length codes for compression of each row of an image. The performance of the Greedy Path Selection Algorithm, as explained in [6] has been marginally better than many other near lossless schemes but low complexity is its main advantage.

In this paper a near lossless scheme is proposed which uses local packing of an image histogram's bins. After setting an error tolerance, we group histogram bins into a number of small groups and then pack each group into a single bin. Groups are formed within tolerable error constraints. This packing is equivalent to near lossless image formation. We prove that our packing scheme produces minimum entropy histogram. The proposed method will be used in conjunction with a lossless scheme to achieve better compression ratios. In section 2 of the paper we explain the packing scheme and the proposed compression method. In section 3 simulation results are presented and the proposed method is compared with other standard methods. Concluding remarks are offered in section 4 of the paper.

2. PROPOSED NEAR LOSSLESS METHOD

Considering image I, by changing the intensity of pixels of I within the permissible range of Equation 1, the entropy of image changes.

$$\left| I(i,j) - \tilde{I}(i,j) \right| \le M \qquad (1)$$

In Equation 1 variables $I(i, j)$ and $\tilde{I}(i, j)$ respectively indicate an original intensity of a pixel and the altered pixel value. The change that occurs in the image may cause an increase or a decrease in the entropy of the image. Here we intend to offer an algorithm for changing the intensity of pixels in a manner that reduces the overall entropy of the image. Considering M=1 in Equation 1, each pixel could get one of three intensities. Hence, for an image with 512×512 pixels there are about $3^{512\times512}$ possible image configurations. To find a way to decide which of these configurations give minimum entropy the following argument is laid down. Changing intensities of pixels is equivalent to combining bins of the histogram of the image by transferring a bin, partially or totally, to an adjacent bin.

Proposition 1: what portion of a histogram bin should be transferred over to adjacent bins to achieve minimum entropy?

Let us consider the sample histogram of Figure 1(a). Parts (b) and (c) of Figure 1 show different cases of transferring a bin to its adjacent bins.

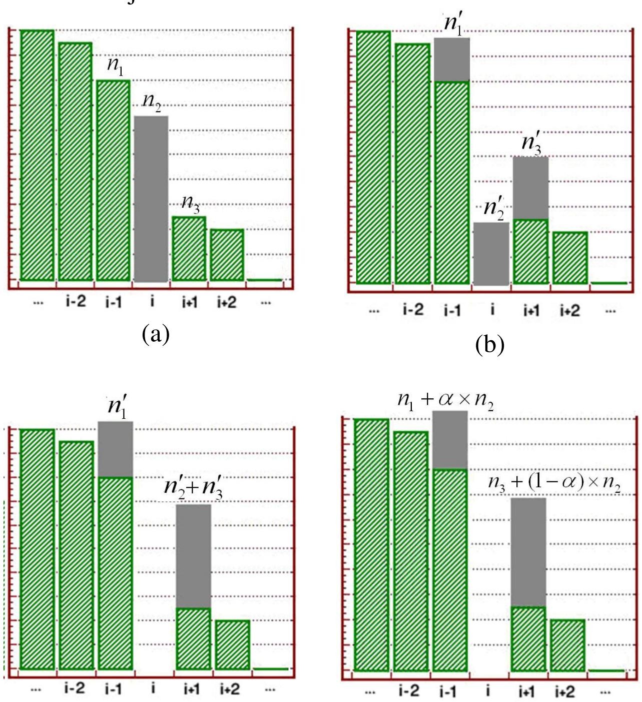

Figure 1. (a) original histogram, (b) partial transfer of a bin to two adjacent bins, (c) total assimilation of a bin, (d) portioned assignment of bin i to adjacent bins.

In Figure 1(a) variables n_1, n_2, and n_3 are the populations of three adjacent bins. In Figure 1(b) a part of bin i has remained in tacked and the rest of it has been transferred to the adjacent bins. On the other hand, Figure 1(c) shows a case where bin i has completely been transferred, as two distinct parts, to the two adjacent bins. Entropy of Figure 1(b) is shown in Equation 2 and that of Figure 1(c) is given by Equation 3.

$$E_1 = e - (n_1'/S)\log(n_1'/S) - (n_2'/S)\log(n_2'/S) - (n_3'/S)\log(n_3'/S) \qquad (2)$$

$$E_2 = e - (n_1'/S)\log(n_1'/S) - ((n_2'+n_3')/S)\log((n_2'+n_3')/S) \qquad (3)$$

In the above two equations e is the entropy of other bins and S is the total pixels of the image. From Equations 1 and 2 we can conclude that

$$-((n_2'+n_3')/S)\log((n_2'+n_3')/S) \le -(n_2'/S)\log(n_2'/S) - (n_3'/S)\log(n_3'/S) \qquad (4)$$

This means that

$$E_2 \le E_1 \qquad (5)$$

Therefore, to obtain a histogram with minimum entropy, through application of Equation 1, either a histogram bin should be left in tacked or it should be completely transferred to adjacent bins.

Proposition 2: If a bin is to be transferred, what portion is transferred to the bin with higher intensity and what portion to the bin with lower intensity?

Figure 1(d) shows an example of transferring α percent of a bin to one side and the rest to the other side. We need to find an α which minimizes the entropy.

The entropy of the histogram of Figure 1(d) after the bin transfer can be expressed as a function of α according to Equation 6.

$$E = e - ((n_1+\alpha*n_2)/S)\log((n_1+\alpha*n_2)/S) - ((n_3+(1-\alpha)*n_2)/S)\log((n_3+(1-\alpha)*n_2)/S) \qquad (6)$$

Equations 7 and 8 show the first and second derivatives of the above function.

$$E' = -(n_2/S)\log((n_1+\alpha*n_2)/S) - n_2/(S*\ln 2) + (n_2/S)\log((n_3+(1-\alpha)*n_2)/S) + n_2/(S*\ln 2) \qquad (7)$$

$$E'' = -n_2^{\,2}/(\ln 2*(n_1+\alpha*n_2)) - n_2^{\,2}/(\ln 2*(n_3+(1-\alpha)*n_2)) \qquad (8)$$

Since Equation 8 is always negative it means that E as a function of α is concave downward. This means that minimum value of E is either at the beginning or end of the possible values of α. Hence, minimum entropy either occurs at $\alpha = 0$ or $\alpha = 1$. In another words, when transferring a bin to adjacent bins, the whole bin should be transferred to only one of the adjacent bins. Therefore, for every bin of a histogram we can have one of the three below choices:

1-Bin is not transferred.

2-Bin is completely transferred to the right.

3-Bin is completely transferred to the left.

We can generalize this argument for other values of M beside M=1.

Based on the above two propositions an algorithm is proposed for local packing of histogram for a certain M constraint. For the case of M=1 the number of all combinations that bins of a histogram could have is about 3^{256}. This is for a case that 8-bit grayscale pixels are considered in an image. To find combinations that produce minimum entropy we use a graph. A partial sample graph is shown in Figure 2. Every bin of the histogram is equivalent to a node in the graph. An arc in the graph represents the group packing of the node, which the arc originates from, with all those nodes that the arc jumps over them. Every path on the graph, which starts from the node at the very left of the histogram, goes through a number of nodes and will end at the node at the very right of the histogram. Therefore, every path represents a certain combination of locally group-packed bins. Referring to Figure 2, as an example, a path is shown with dotted arcs. This indicates packing of bins 0, 1, and 2 as one group, and packing bins 3 and 4 as another group. For packing of bins 0, 1, and 2, based on Equation 1, bins 0 and 2 should be transferred to bin 1. On the other hand, for packing bins 3 and 4 two choices exist: either transfer bin 3 to 4 or transfer bin 4 to 3. The resulting entropy from either of these two choices is the same. Now, a path should be selected (from a large collection of possible paths) to minimize the overall entropy of the resulting locally packed histogram. All of the arcs in the graph are labeled with the local entropy that will result from packing of the bins that the arc indicates. Using the Viterbi algorithm [9] we can select a path on this graph with minimum entropy.

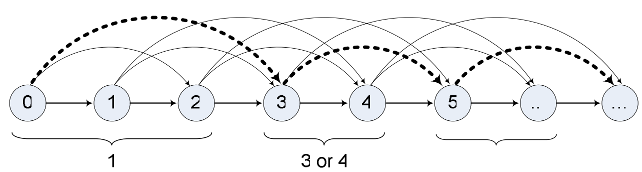

Figure 2. An example of graph formation for M=1.

The effects of local packing of histogram bins are shown in Figure 3 where in the top-left we have the original histogram and the other histograms are formed based on different values of error tolerance, M.

The proposed local packing of histogram bins (LPH) changes the intensities of some of the pixels within a specific error tolerance. The proposed method minimizes the histogram entropy. This in turn, within the mentioned constraints, produces an image with minimum entropy. We can apply the proposed method to serve as a preprocessing block of a lossless compression unit to obtain an efficient near lossless compressor. This preprocessor while reducing the entropy increases spatial correlation among many neighboring pixels. Hence, the compression ratio of the lossless block increases, too. The overall block diagram of our scheme is shown in Figure 4.

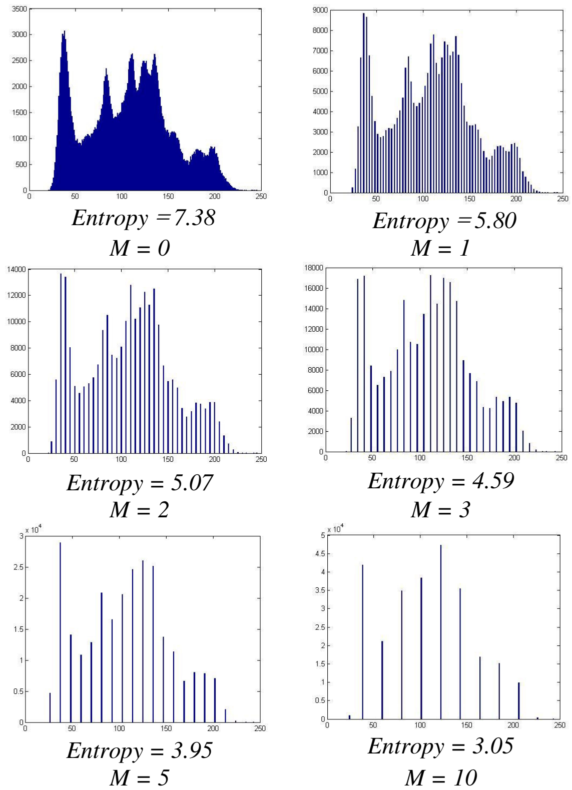

Figure 3. Effect of application of LPH method to a histogram.

To study the effects of the lossless compression block on the overall performance of the algorithm two different lossless schemes are used in final block of Figure 4. In one case the final block of Figure 4 consists of median edge detection (MED) predictor where the produced prediction errors are encoded by Huffman coding. We call this scheme as LPH+MED. On the other hand we can place a very efficient lossless compression scheme such as JPEG-LS inside the last block of Figure 4. We refer to this combination as LPH+JPEGLS. In the following section we compare our proposed method with a number of standard near lossless schemes such as CALIC, JPEG-LS (with error tolerance), and methods of references [3], [6] and [8].

3. SIMULATION RESULTS

In Table 1 the implementation results for the proposed LPH+MED and LPH+JPEGLS are compared with a number of standard near lossless schemes. Also, results from a number of schemes proposed in the literature are presented. For any value of tolerable errors, M, the hybrid LPH+JPEGLS has been superior to LPH+MED. This is due to the efficiency of the JPEG-LS. Considering the low complexity of the proposed LPH and low overhead that it imposes, we see that for any value M the hybrid LPH+JPEGLS performs better than JPEG-LS. It should be reminded that JPEG-LS, used in table 1, is the near lossless version and the one used in the proposed hybrid algorithm is lossless. This means that LPH preprocessor, with small overhead, can improve the performance of the near lossless JPEG-LS algorithm. Also, the algorithm of reference [8], despite its high complexity and iterative nature, for small values of M is inferior to the LPH-JPEGLS algorithm. For small values of M the proposed hybrid LPH-JPEGLS outperforms that of reference [3]. The obtained results from the proposed method are very much comparable with those of CALIC, while the proposed method has lower complexity than CALIC. For any value of M the proposed method outperforms the algorithm of reference [6].

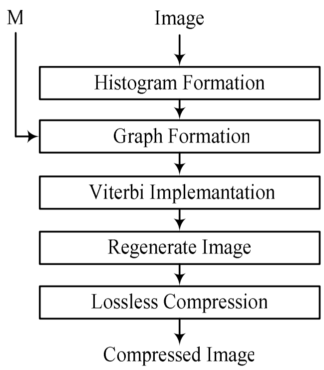

Figure 4. Block diagram of propose method.

4. CONCLUSION

In this paper we proposed an algorithm for near lossless compression. An input image was used to produce a histogram. A tolerable error threshold is required in any near lossless scheme. We proved in this paper that, within the set error constraint, a histogram could be produced with minimum entropy. This was done by packing of histogram bins. Hence, we were able to reconstruct a near lossless image with minimum entropy. The reconstructed image was then fed into a lossless image compressor to achieve an efficient near lossless scheme. The proposed method was hence proved to be capable of converting any lossless scheme into a near lossless one. Experimental results showed acceptable results as compared with standard schemes as well as schemes presented in the literature.

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6. REFERENCES

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Table 1. Comparison of proposed method with other compression schemes

		M=0		***M=1***		***M=2***		***M=4***		***M=6***	
	Method	***BPP***	***PSNR***	***BPP***	***PSNR***	***BPP***	***PSNR***	***BPP***	***PSNR***	***BPP***	***PSNR***
Lena	***LPH +MED***	4.40	∞	2.89	49.89	2.30	45.12	1.74	39.91	1.55	36.74
	LPH +JPEGLS	4.25	∞	2.53	49.89	1.95	45.12	1.43	39.91	1.18	36.74
	JPEGLS[5]	4.25	∞	2.72	49.90	2.09	45.15	1.54	40.11	1.24	36.99
	CALIC[4]	4.10	∞	2.59	49.89	1.95	45.16	1.29	40.27	0.96	37.21
	REF[3]	4.30	∞	2.77	49.89	2.12	45.17	1.36	40.56	0.92	38.56
	REF[8]	N.A	∞	2.69	49.89	2.02	45.16	1.28	40.59	0.86	38.54
	REF[6]	4.49	∞	3.16	49.00	2.81	43.91	2.40	40.00	2.15	36.70
Barbara	***LPH +MED***	5.06	∞	3.84	49.88	3.21	45.11	2.48	39.89	2.13	36.73
	LPH +JPEGLS	4.86	∞	3.18	49.88	2.55	45.11	1.93	39.89	1.57	36.73
	JPEGLS[5]	4.86	∞	3.30	49.89	2.65	45.14	2.02	40.04	1.67	36.99
	CALIC [4]	4.59	∞	3.07	49.89	2.42	45.14	1.77	40.11	1.40	37.21
	REF [3]	4.90	∞	3.38	49.90	2.72	45.16	1.97	40.52	1.52	38.56
	REF[8]	N.A	∞	3.31	49.89	2.65	45.17	1.91	40.54	1.48	38.59
	REF[6]	5.2	∞	4.2	49.00	3.54	43.94	2.83	40.05	2.07	36.64