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Progressive Error-Diffused BI-Level Image Compression Coding Using Bayes Theorem

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Abstract: This study proposes a new methodology for Error diffused bi-level image compression algorithm. The existing JBIG shows relatively low performance in compressing error-diffused bi-level images. The new method suggests Bayes theorem for showing high performance in error diffused bi-level image compression. By doing so we can improve the resolution and compression factor of the error diffused bi-level images. This method is quite fruitful when we use error diffused bi-level images in the file.

Key words: Joint bi-level image expert group, Bayes theorem, probability estimator, lossless compression

INTRODUCTION

Advances in digital technology and increasing uses of multimedia applications. Image compression requires the higher performance, to address the needs and requirement of multimedia and Internet applications (Konda *et al*., 2002). Thus, many researchers have developed data compression technologies in order to use media resources more efficiently. Among the various compression methods, Swanson and Twefik (1996) and Gurcan *et al*. (1999) developed wavelet-based compression algorithms for bi-level images. Wavelet decomposition generally reduces total number of black or white dots in simple images (Panda *et al*., 2000). However, wavelet-based algorithms do not work well for halftone images because they have many transitions between black and white dots. Langdon used an arithmetic coding for compression of bi-level images (Langdon and Rissanen, 1981a). They combined a "context" algorithm (Langdon and Rissanen, 1981b) and an arithmetic-coding algorithm. Many researchers have used the context algorithm for modeling image data and the arithmetic coding for compression (Nguyen and Weinricher, 1996; Reavy and Boncelet, 1997). The current international standard, the Joint Bi-level Image Experts Group (JBIG), is a representative of a bi-level image compression algorithm (Daniel, 2000). But it shows relatively low performance in compressing error-diffused halftone images. The proposed methodology is based on Bayes theorem. Here the proposed coding procedure compresses the error diffused bi-level image in 2 steps: First, it groups 2×2 dots (4 dots) in to a cell and using Bayesian probability estimator it represents the cell using two values such as S-value (sum of the dots) and C-value (binary representation of the cell). Second, using S-value and C-value it encode and decode the error diffused images with good performance. The quality of images reconstructed from the proposed method is better than one reconstructed from layer 1 of the compression coding of the JBIG.

BAYES THEOREM

The general outlook of Bayesian probability, promoted by Laplace and several later authors, has been that the laws of probability apply equally to propositions of all kinds. Advocates of logical (or objective epistemic) probability, hope to codify techniques that would enable any two persons having the same information relevant to the truth of an uncertain proposition to independently calculate the same probability (Habson, 2003). Except for simple cases the methods proposed are controversial. Using the total probability, if $B_1, B_2 \ldots\ldots\ldots B_n$ are a set of mutually exclusive and exhaustive set of events, then,

$$P(A) = \sum_{n=1}^{N} P(A/B_n)\, P(B_n) \qquad (1)$$

therefore,

$$P(B/A) = \frac{P(B)P(A/B)}{\sum_{n=1}^{N} P(A/B_n)\, P(B_n)} \qquad (2)$$

Bayes theorem is called as the rule of inverse probability.

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PROGRESSIVE BAYESIAN COMPRESSION ALGORITHM

The proposed algorithm is described by two equations, where one is for coding and other is for probability estimation. The progressive Bayesian compression method has the following steps:

- It groups 2×2 dots in to a cell.
- Each cell is represented by two values such as S-value and C-Value.
- The C-value is binary representation of the dots in the cell, the C-value of t^{th} cell as x_t represented as follows;

  $x_t = d_0(t)d_1(t)d_2(t)d_3(t)$, Where $d_i(t)$ is the i^{th} dot value in the t^{th} cell, which is a bi-level value, 0 or 1. C-value is an element of the set C={0000,0001….1111),whose element is a four-digit binary number.

- The representation of a cell value is S-value, which is sum of dots in the cell, where the letter "S" is the initial for "sum". We denote S-value by l as follows

$$l(xt) = \sum_{i=0}^{i=3} d_i(t) \quad (3)$$

S-value is an element of the set S = {0,1,2,3,4).It can be thought of as a smooth filtered value of the cell

- The ideal code length of a symbol stream with length T can be calculated by the following equation:

$$L(x_t) = -\sum_{t=1}^{T} \log (p(x_t) \quad (4)$$

Where x → is the symbol stream with length T to be encoded; L(x) → is the total code length to represent the symbol stream x; $p(x_t)$ → is the probability mass function of the t^{th} symbol x_t in the symbol stream x and the base of log is 2.

- The exact probabilities of x_t may not be known. So, the exact probabilities of x_t and its code length should be estimated as follows;

$$\tilde{L}(x) = -\sum_{t=1}^{T} \log (\tilde{p}(x\ t)) \quad (5)$$

Where $\tilde{p}(x_t)$ → is the estimated pmf of x_t that is estimated from the previous symbols before x_t in the stream. If we use Bayes' theorem, then finally we get the total code length equation is as follows:

$$L(x) = [-\sum \log \tilde{p}(C_j)] + [-\sum \log \tilde{p}(x_t/C_j)] \quad (6)$$

Equation 6 shows that the total code length of a symbol stream is equal to the sum of two terms: the first term represents the code length of-value and the second term represents the code length of-value with the given-value. Therefore, the encoding process can be divided into two passes:

- In order to estimate the probability distribution of $p(x_t)$,we use a Bayesian estimator in the proposed algorithm. In addition, we can exploit the conditional probability with the S-value of neighbor cells. We estimate the probability using the following equation:

$$p(x_t \in Ck|CX(s)) = \frac{n_{cx(s)}(k)+1}{\sum n_{cx(s)}(i)+N_s+1} \quad (7)$$

Where $n_{cx(s)}(k)$ → denotes how many times the symbol rx_t such that $l(x_t) = k$ occurred so far with a given

- The conditional probability is estimated and updated from the sequence of cells as follows;

$$\tilde{p}(x_t = h \,||\, x_t \in C_k, CX(d', 1) = \frac{n_{cx(d',\ l)}(h)+1}{\sum_{i \in Ck} n_{cx(d',\ l)}(i)+N(C_k)} \quad (8)$$

Where $n_{cx(d',l)}$ (h) → denotes how many conditional events ($x_t = h$, when $x_t \in C_k$) occurred so far with the context CX(d',l) ; N(Ck) → is the number of elements in C_k In (8), the initial probability was set as an uniform distribution of $1/N(C_k)$ for coding of the first symbol of each case. With these estimated probabilities, we use an proposed coding algorithm to compress bi-level images.

ENCODER AND DECODER BASED ON PROPOSED ALGORITHM

Encoder: Figure 1a shows the block diagram of the encoder. The encoder scans an image twice to encode it by using the two-pass method. First, the S-value of cell is encoded without information loss. So, that is the number of block dots and white dots are preserved in the first pass. However, the information about the exact positions of dots in a cell is lost. This is the reason why we named the first pass near-lossless compression. The block of the

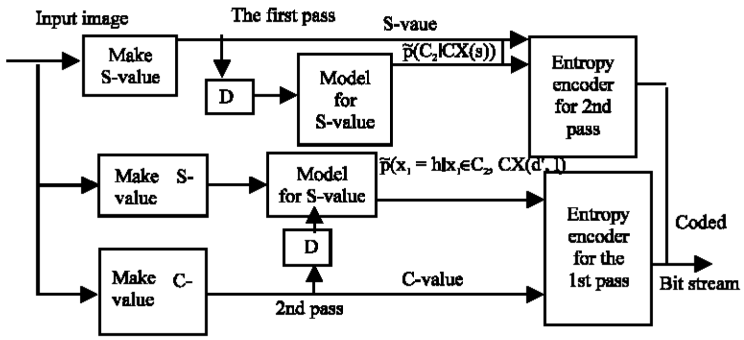

Fig 1a: Block diagram of the proposed encoder

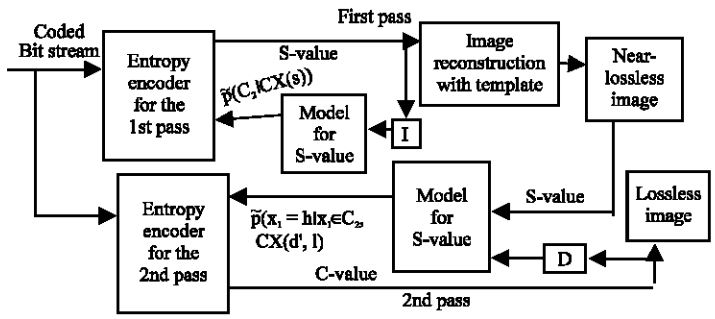

Fig 1b: Block diagram of the proposed decoder

"Make S-value "in Fig. 1b rearranges the image and generates S-value. The probability of S-value is estimated in the block of the "Model for S-value". After a cell is encoded, the probability is updated by the encoded cell, so that it can be updated at the decoder in the same way as the encoder. The S-value and its probability are sent to the entropy encoder block.

In a second pass, the C-value is encoded using the S-value that is encoded in the first pass and the C-value context. The probability of the corresponding C-value is estimated in the block of the "Model for C-value ". The context for theC-value must be causal like the S-value context.

Decoder: The Fig. 1b shows the block diagram of the proposed decoder. All procedures except the S-value frame buffer are exactly the reverse of the encoding procedure. When the first pass is completed, we can know only the number of dots in a cell, not the exact location of dots. Therefore, we can reconstruct images using predetermined templates when an S-value is determined.

However, if we use only one of such templates to reconstruct the image, images suffer from artifacts caused by the granularity or the periodicity. This reduces the advantage of the error diffusion algorithm. To reduce these artifacts, we made a table for the arrangement. From error-diffused images, we investigated the patterns using 256 ($=2^8$) C-value context. There are 5 S-value for each context. Because there is only one pattern in the case of the zero or 4 S-value of 1, 2 and 3. For each value with a specified context, we counted how many times each pattern occurred. With those counts, we made a table of the most probable patterns for each S-value. We reconstructed the exact image using the table after decoding pass. In the second decoding pass, we reconstructed the exact image using the C-value with the information decoded in the first pass. The second pass is a kind of refinement step, that is, the exact location of dots in every cell is determined.

MATERIALS AND METHODS

The proposed algorithm was implemented in MATLAB 6.0 and tested on Intel Pentium 4 with 1 GB RAM, running windows 2000.

The pseudo code for the proposed algorithm is as follows:

- Initialization
- Read the input image in the variable a
  a = imread ('rice.tif');

```
Convert it into a black and white image
Z = im2bw(a);
```

- Adding noise with the density of 0.05 to the image Z and store it in a variable b.

```
b = imnoise (Z,'salt and pepper',0.05);
```

- Find the probability of S0…S4 (S-value)

```
for I = 1: 255; for j = 1:255;
C(i,j)=[b(i,j)+b(i, j+1)+b(i+1, j)+
            b(i+1, j+1) ];
if ( C(i,j) = = 0)
            D(i, j)=0; p = p+1;
else if ( C(i, j ) = = 1)
            D(i, j) = 1110; q = q+4;
            ……….
            continue; end
```

- Total number of bytes required for S-value is

```
A = (p+q+r+s+t);
```

- Find the probability of d0…d15 (C-value)

```
            for i = 1: 255; for j = 1: 255;
c = [b(i, j)]; w = [ b(i, j+1)];
x = [ b(i+1, j)]; y = [ b(i+1, j+1)];
if(c = = 0 and w = = 0 and x =  =0 and y = = 0)
d = d+1;
if(c = = 0 and w = = 0and x = = 0 and y = = 1)
e = e+1;
………..
continue; end
```

- Total number of bytes required for C-value is

```
total = ( D+E+F+G+H+I+J+K+L
+M+N+O+P+Q+R+S+T+U);
```

- Calculate the S-Value compression ratio: (in first pass)
  a = no. of bytes required for input image
  A = no. of bytes required for S-value
  S-Value compression ratio is S = (a/A).

- Calculate the C-Value compression ratio: (in second pass)
  a = no. of bytes required for input image.
  total = no. of bytes required for
  C-value
  C-Value compression ratio is
  C = (a / total);

In our experimental analysis, using this pseudo code, we tested 5 Bi-level images and displayed their results.

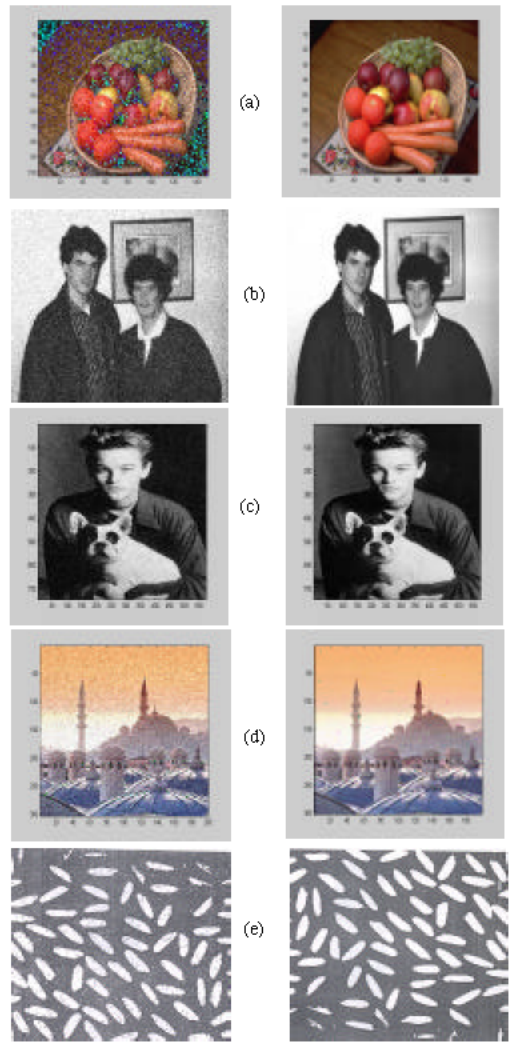

Fig. 2: Reduced test images for printing. (a) Image no. 1, (b) Image no. 2 and (c) Image no. 3. (d) Image no. 4, (e) Image no. 5

RESULTS AND DISCUSSION

For the experiments, we generated 5 bi-level images as shown in Fig. 2, whose sizes are 4768×6912 for no.1, 6912×4768 for no.2, 4768×4011 for no.3, 3200×1996 for no.4 and 3072×2304 for no.5.

Comparison of compression ratios: For the comparison of the compression ratios, we compressed the five test images using the proposed algorithm and the JBIG. The first layer JBIG is a lossy coding because we reduced the dimension of the images. In addition, we encoded the images with a sequential coding of the JBIG that fully codes an image in a single resolution layer without

Table 1: W-SNR of the decompressed images from the Pass-1 of the progressive coding of the JBIG and the proposed method

Image	JBIG	Propsed algorithm
1	9.95	17.78
2	10.66	17.88
3	18.07	25.36
4	13.32	24.09
5	14.58	22.64

Table 2: Comparison of compression ratios of both JBIG and proposed algorithm

	JBIG with two Pass		Proposed algorithm	
Image	Pass-1	Pass-2	Pass-1 Near lossless	Pass-2 lossless
1	6.00	1.51	3.57	1.90
2	6.34	1.61	3.41	1.95
3	8.76	2.12	4.62	2.70
4	8.87	2.20	4.16	2.62
5	7.06	2.79	5.34	4.56

reference to any lower resolution images (CRPAI, 1993). When we compress bi-level image using the sequential coding of the JBIG, it does not reduce the resolution of an image and compresses the image with a template. Because error-diffusedbi-level images are specially compressed and do not have low frequency graininess, the compression ratios from the sequential coding of the JBIG are higher than those from the progressive coding of the JBIG. The compression ratio of each algorithm is shown in Table 1. If we compress images using the sequential coding of the JBIG, it is impossible to decompress them progressively. To decode images progressively, we must encode them with progressive coding of the JBIG or with other algorithms such as the proposed algorithm. When two progressive coding algorithms are applied to error-diffused images, the proposed algorithm works better than the progressive coding of the JBIG. In addition, the compression ratios of the proposed algorithm are higher than those of the sequential coding of the JBIG.

Comparison of the decompressed image quality: We compressed the image with quality, when the images are reconstructed such as the first pass of the proposed method and the layer 1 of the progressive coding of the JBIG. The compression ratios of the two methods are different and they are not adjustable.

For the image quality comparison, we measured the Weighted Signal to Noise Ratio (W-SNR) (Lin, 1993) that is, the ratio of the average weighted signal power to the average weighted noise power and it was given in Table 2. We also briefly analyzed the computation complexity of the proposed method in comparison with the JBIG in Table 2. The computation complexity of the proposed method is longer than that of the JBIG (Lin, 1993) because of the two pass structure of the proposed algorithm.

CONCLUSION

This algorithm proposed a bi-level image compression method with two passes. The sum value (S-value) of the cell is encoded in the first pass and the cell value (C-value) is encoded in the second pass. The proposed method is designed on the basis of Bayes theorem. When we compress the error-diffused bi-level images without information loss using two passes of the proposed method, it is comparable to the JBIG's. The quality of images reconstructed from the first pass of the proposed method is better than one reconstructed from layer 1 of the progressive coding of the JBIG.

As per the literature survey, if the compression ratio is lie between 4-5, then it represents lossless compression. Hence here we have the maximum compression ratio 4.6, so it becomes lossless compression.

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