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# A Still Image Compression Scheme with Joint Probability Based Scanning of a Bit Plane Using Golomb-Rice Code

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**Abstract: In this paper, a modified JPEG2000 still image compression system has been proposed. A three level decomposition of Daubechies 9/7 Discrete Wavelet Transformation has been first applied to the entire input image. Then, scalar quantization is used to decrease and round off the transformed coefficients. The quantized coefficients are then subjected to bit modeling in each bit plane. A joint probability statistical model based significance selection has been proposed to select the significant bit for entropy coding with two scan coding technique. In this proposed work, after selecting all the significant bits in a particular bit plane, a geometrically distributed set of context is modeled and subjected to encode with Golomb-Rice coding to give compressed data. The decompression is effected with a simple, respective inverse operation. The proposed system has been experimented with standard benchmark images and the standard performance measures, Compression Ratio and Peak-Signal to Noise Ratio are used to evaluate the result.**

**Keywords: Bit-plane modeling, Geometrically distributed, Golomb-Rice coding, JPEG2000, Peak-Signal to Noise Ratio (PSNR), Scan coding.**

## I. Introduction

Due to high demand of multimedia storage and transmission over the wireless mobile environment [9], scalability of the system becomes a continuous research field. Also Statistical modeling of data plays a significant role to manipulate the system before implementation. Many applications in image processing require a prior probability model. This is especially true for the application of image compression [20] [21], in which the performance limits of an algorithm are determined by the underlying prior statistical model. For the image compression, if intensity is modeled as bit by bit on each layer [32] adaptively, it leads system to be more scalable [10]. Based on the probability of contribution of a bit, entropy is calculated. The entropy value of a bit reflects the information it has. In image compression, entropy encoding [3] plays major role. Compression standard JPEG2000 is richer in its functionality [8] [22] [28] than other compression standard but not widely accepted because of its higher execution time as well as some degradation in reconstructed image quality like blurring effect at low intensity value.

The prior knowledge of probability distribution of data helps to model the system and also improves the performance [33]. The probability distribution of sequences of symbols being encoded in image compression algorithms like JPEG-LS [27] and FELICS [24] [25] reduces the complexity of the system and provides good result. One of the entropy coding, Golomb-Rice coding algorithm described in [1] [2] [10] achieves higher coding efficiency than other entropy coding due to its lack of dependence on a codeword table and less complexity from both software as well as hardware perspective [11]. Also Golomb-Rice [6] coding gives best result in case of geometrically distributed data. So, in this proposed work, JPEG2000 is studied at each micro level and models data at each bit plane in geometric distribution so that Golomb-Rice algorithm fits into model. Based on the relation among the bit planes in a context, a joint probability distribution [21] model is utilized to improve the performance of JPEG2000.

The goal of the proposed technique is to design a compression system based on the statistical probability distribution of data comparable with JPEG2000 compression standard.

## II. Related Works

Yair Wiseman discussed about the original JPEG and JPEG2000 in [30]. JPEG divides the entire image into (8×8) blocks and uses Discrete Cosine Transform (DCT) to work in frequency domain. Quantization has been then used as lossy compression and then subjected to Huffman entropy coding. JPEG2000 employs two different wavelet transforms – an irreversible transform that depends on the precision of the decoder and sets a scalar quantization [12] [17] according to this precision and a reversible transform that makes use of only integer coefficients. Clearly integer numbers do not need rounding; therefore this transform does not use any quantization and thus this transform is used for lossless coding. Major modification in JPEG-2000 has been done compared to JPEG. The designers of JPEG-2000 have came to a decision to depart from the block based DCT coding used by the traditional JPEG and MPEG standards in favor of a wavelet based compression. The DWT provides improved quality than JPEG and also provides Region of interest coding [16] [32].

JPEG 2000 also improves a user's ability to interact with an image. The zoom, pan, and rotate operations that users increasingly expect in networked image systems are performed dynamically, by accessing and decompressing just those parts of the JPEG2000 code stream, which contain the compressed image data for the region of interest [22]. This new standard had several goals: improve on existing standards; serve the needs of high-end and emerging applications; and open up new markets and opportunities for image compression.

C Chrysafis *et al.* [4] and Zhen Liu *et al.* [33] focused on the Context-based coding that has been widely adopted in image and video compression and is a key component of the new JPEG2000 image compression standard also. Based on the correlation among the wavelet coefficients in each context, a conditional probability model has been introduced to reduce the coder complexity. In [7] [8] David Taubman explained about the Embedded Block Coding with Optimized Truncation (EBCOT) as the basis for the JPEG2000 image compression standard. The EBCOT image compression algorithm offers state-of-the-art compression performance together with an unique set of bit-stream features, including resolution scalability, SNR scalability and a random access capability i.e. Region of Interest (ROI). All features can exist within a single bit-stream without substantial sacrifices in compression efficiency. The EBCOT algorithm also introduces the concept of abstract quality layers which are not directly related to the structural properties of the underlying entropy coder. Also Minsoo Rhu *et al.* [19] discussed about the complexity in Embedded Block Coding with Optimized Truncation (EBCOT) employed in the JPEG2000 standard. It mainly shows the account for the majority of the processing time, because the EBCOT is full of bit operations that cannot be implemented efficiently in software.

Rong Zhang *et al.* [23] stated that the Compression ratio and computational complexity [5] are two major factors for a successful image coder. By exploring the Laplacian distribution of the wavelet coefficients, a bit plane entropy coder has been reported here. Paul G. Howard *et al.* [20] explained about arithmetic coding, showing how it provides nearly optimal data compression and how it can be matched with almost any probabilistic model.

Tung Nguyen *et al.* [26] discussed about combination of simple variable-length codes and Context-Adaptive Binary Arithmetic Coding (CABAC), which yields the same coding efficiency as the JPEG2000 transform coefficient coding at a lower complexity level. A reduced complexity method for coding the absolute transform coefficient levels using the CABAC framework has been described.

Chang-Hoon *et al.* [5] designed a low-complexity Embedded Compression (EC) algorithm for the JPEG2000 encoder to efficiently reduce memory requirements. Through the EC technique, memory requirement for intermediate low-frequency coefficients during multiple DWT stages are reduced by a factor of 2 compared with direct implementation of the JPEG2000 encoder. Furthermore, this EC reduces the size of code-block memory from DWT to Bit Plane Coder (BPC). The EC can be applicable to the JPEG2000 encoding system to save memory size and bandwidth requirements with minor picture quality degradation.

Henrique S. Malvar [10] reported a encoding of Generalized Gaussian (GG) sources after quantization with uniform scalar quantizers with deadzone. Z. Xiong *et al.* [31] reported a space frequency quantization in wavelet based image coder, which are good source models in multimedia data compression. For a wide range of source parameters, the Run Length Golomb-Rice (RLGR) encoder has a performance close to that of the optimal Golomb-Rice and Exp-Golomb coders designed with knowledge of the source statistics, and in some cases the RLGR coder improves coding efficiency by 20% or more. The run mode of the RLGR coder increases its efficiency for sources with Probability Density Function (PDF) highly peaked at the origin, such as in low bit-rate coding or other scenarios that are appropriately modeled by generalized Gaussians with low shape parameter.

A. Kiely's [1] reported the use of Golomb-Power-Of-2 (GPO2) codes to sequences of nonnegative integers from a discrete source. Specifically, it showed the interest on the Golomb-Rice entropy coding algorithm. It is derived with a simple method to select the optimum GPO2 code for a geometrically distributed source given the mean value. They have devised a simpler code selection procedure that generalizes previously known methods. The conceptual simplicity of the Rice coding paradigm brings with it some inherent limitations in terms of implementation complexity and compression effectiveness.

This paper is organized as follows. In Section III, we first show that organization of wavelet coefficients in each band to provide different features. In Section IV, quantization is presented. In Section V, context modeling is presented. Section VI deals with the proposed joint probability based mutual information between the bit planes in contexts and the encoded data can be used to measure the optimal performance. In Section VII, the optimality proof is given for the selected parameter (m). In Section VIII, various performance measures are discussed. Experimental results are discussed in Section IX. And finally, we conclude the paper in Section X.

## III. Analysis of DWT Coefficients

Signal transformation is the procedure of mapping a signal from one domain, such as the original pixel domain, onto another one, such as the frequency domain. When a signal is transformed from spatial domain to frequency domain, it becomes more stationary in each frequency band and easier to code as each coefficient provides local information of the frequency. DWT is a special kind of linear transform which decomposes an image into a number of resolutions in which, the intensity of the image is passing through a set of two filters, one which creates a down sampled version of the original pixel values, and another creates up sampled detail. This two-dimensional transform then repeated on the LL subband to decompose it into four subband layers to support multi-resolution approach. Each iteration creates a new subband level consisting of an LL, LH, HL, and HH subband [13-15].

In the proposed work, bi-orthogonal Cohen-Daubechies-Feauveau (CDF) wavelet is used with 9/7 filter banks. The input signal x(n) is filtered with two mirror filters: Hp(ω) and Gp(ω), where Hp(ω) is a low-pass filter, Gp(ω) is a high-pass filter, p is a wavelet order and n=0,1,.... The output U1 of the low-pass filter H(ω) is called approximation and the high frequency output Y1 from G(ω) is called detail. The outputs of both filters are decimated by factor 2.

$$H_p(\omega).\,(G_p(\omega+\pi))' = 2((1+\cos\omega)/2)^p.$$

$$\sum_{k=0}^{p-1}(p+k-1_{c_k})\left(\frac{1-\cos\omega}{2}\right)^k. \quad (1)$$

where: Hp(ω) - power frequency response low-pass filter,
Gp(ω) - power frequency response high-pass filter,
p - the coefficient which depends on wavelet,
ω - frequency,
(Gp(ω + π))′ - complex conjugate of Gp(ω + π) .

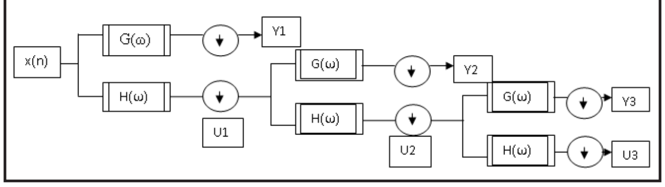


Fig. 1: Decomposition of Wavelet Coefficient

The coefficient is computed in Z-domain using equation (2),

$$H_p(z).G_p(-z^{-1}) = 2\left(\frac{z^{-1}}{4}\right)^p .(1+z)^{2p}\sum_{k=0}^{p-1}(p+k-1_{C_k})$$

$$\left(-\frac{z}{4}+\frac{1}{2}-\frac{z^{-1}}{4}\right)^k. \quad (2)$$

## IV. Quantization

Quantization is the process by which the coefficients are reduced in precision. In the proposed system, this operation has been performed on the transformed coefficient and leads to lossy compression. Each of the transform coefficient $U(x,y)$ of the each sub band is quantized to the value $V(x,y)$ according to the formula given in equation (3).

$$V(x,y) = \left\lfloor \frac{|U(x,y)|}{\Delta} \right\rfloor \operatorname{sgn} U(x,y) \quad (3)$$

where, Δ is the quantizer step size. If the value of Δ is taken to be 1, no quantization has been performed. So, in order to quantize the transformed coefficient the taken quantizer step size must be greater than 1.

## V. Proposed Scan Order of Bit Planes for Significant Bit Selection

In this paper, the aim of proposed system is to adaptively model the bit planes based on the probability distribution of the total bits in the current bit plane. Therefore, the quantized coefficient is decomposed into N number of bit planes, where N depends on the image depth, ranging from Nth bit plane for Least Significant Bit (LSB) to 1st bit plane for the Most Significant Bit (MSB). The Nth bit plane contains all the lowest order bits in the pixels comprising the image and 1st bit plane contains all the higher order bits. Decomposition of quantized coefficient $Q(i,j)$ into N number of bit planes is given in equation (4). Bit wise scan has been performed for each bit planes separately, starting from $Q_{b1}(i,j)$ to $Q_{bN}(i,j)$.

$$Q(i,j) = Q_{b1}(i,j) + Q_{b2}(i,j) + \ldots\ldots\ldots + Q_{bN}(i,j) \quad (4)$$

where, $Q_{b1}(i,j)$ to $Q_{bN}(i,j)$ are the N number of bit planes.

In the proposed work, the scanning of the bits is performed in column wise. During first scan, the entire bits of MSB plane are marked as significant. A binary state-variable is used to indicate the significance map. Its entry is initialized to zero, but is set to one, when the relevant value at position *(i, j)* in the first non-zero bit plane is encountered. From the next scan onwards, the previous marked significant bits are considered to decide, whether the particular bit should be considered as significant or insignificant because all the bit planes are mutually dependent on each other. In order to select the significant bits in second bit plane onwards, all the neighbor bit planes, which are already scanned are taken into account. During the scan process, if the selected bit is 1, it is considered as significant. But, if the selected bit is 0, then neighbors scanned bits are checked, if one of the neighbors as shown in Fig. 2 is 1, then the particular bit is also marked as significant.

| | |
|---|---|
| (i+1,j-1) | (i+1,j) |
| (i,j-1) | (i,j) |
| (i-1,j-1) | |

Fig. 2: Arrangement of Neighbors

The significant bits in each bit plane forms a sequence of context, and is geometrically distributed. The distribution is modeled as given equation (5). For a context c, the data is modeled in the geometric probability distribution as:

$$P(x = c) = (1\text{-}p)^k p \tag{5}$$

where, p is the probability of the sequence of the bits in a bit plane and k is the number of runs of a bit.

The modeled context is stored in priority queue based on the probability of the context. Each context is then sent to the Golomb-Rice encoder as discussed in next section. Due to mutual dependence of all the bit plane, the particular bit plane $Q_{b(i,j)}(x, y)$ in $(x,y)$ plane, even though we have the approximate bit probability in geometric distribution the probability of the one bit plane is jointly distributed with the neighbor bit plane's data $Q_{b(i+1,j)}(x,y)$, $Q_{b(i,j-1)}(x,y)$, $Q_{b(i+1,j-1)}(x,y)$ and $Q_{b(i-1,j-1)}(x,y)$ for the particular modeled context. So, the overall real probability of the bit is quite different, which is significantly affected by the neighborhood coefficients.

Therefore, we have modeled the data using joint probability distribution for a context in terms of current bit plane data with their previous and next bit planes for significant bit selection. For N bit planes ($B_1, B_2, \ldots\ldots, B_N$) in a context C, the joint probability function will be:

$$P(b_1, b_2, \ldots\ldots, b_N) = P(B_1 = b_1, B_2 = b_2, \ldots\ldots, B_N = b_N)$$

## VI. Proposed Golomb-Rice Entropy Coding for Context

For each bit plane the data is a single bit stream of length n bits in which, there are r 1s and rest of the bits are 0s. The algorithm makes a sequence of context that always ends with a 1 or 0 based on the Most Probable Bit (MPB) i.e. $0^i\ 1$ and $1^i\ 0$. So, it is considered that each run is, to be of length $L_1$, $L_2$, ……….., $L_r$ respectively. The bit plane is modeled as a sequence of $L_1 1 L_2 1 L_3 1 \ldots\ldots\ldots\ldots L_r 1$ or $L_1 1 L_2 1 L_3 1 \ldots\ldots\ldots\ldots L_r 0$, such that,

$$(L_1 + L2 + L3 + \ldots\ldots\ldots\ldots + Lr) + r = n$$

In the proposed work, Golomb-Rice encoder function takes as input a sequence of context together with their respective probabilities and encode accordingly. Each context is in the form of Geometric distribution, the number of runs $i$ of the most probable bit is taken in the form of $i=qm+r$, where q represents the quotient, r represents the remainder and m is a positive integer. Since, the value of m affects the overall compression rate, in the proposed work, optimal value of m is taken as nearest power of 2 of $p{*}Ln(2)/(1\text{-}p)$ where, $p$ is the probability of MPB in the modeled context.

Procedure:

(1) Take the context and check for the last bit.
    If last bit is 1 then 0 is the MPB in the context.
    If last bit is 0 then 1 is the MPB in the context.
(2) Find the probability $p$ of the MPB in the particular context.
(3) Calculate the value of $p{*}Ln(2)/(1\text{-}p)$ and consider the m value as nearest power of 2 of $p{*}Ln(2)/(1\text{-}p)$.
(4) Calculate the value of log2 m.
(5) Code each $0^i\ 1$ as $1^q\ 0\ y$ and $1^i\ 0$ as $0^q\ 1\ y$, where,
    $i=qm+r$; $0 <= r < m$ and $y$ is the binary coding of r, using log2 m bits.
(6) The final coded bit stream is: MPB code1 code2 ... code n tail bit.

where,

MPB: 1 bit value of the most probable bit.

$code_j$: The code of each context.

tail bit: A single bit that is 1 if the last bit is 1; it is 0 if the last bit is 0.

## VII. Proof for the Optimality of Selected Parameter m

In this proposed work, it is clear that, based on the most probable bit the context is made. The code model is in the form of either $0^i 1$ and $1^i 0$, where $i$ be the number of runs of MPB and it can be any random variable that takes on values in {0, 1, 2, ...}. For the model in the form of $0^i 1$, the probability distribution is:

$$P[i = n] = P[1st\ bit = 0]P[2nd\ bit = 0]\ldots P[nth\ bit = 0]P[(n + 1)st\ bit{=}1]$$

$$P[i = n] = p^n (1\text{-}p)$$

The average of $i$ is

$$E(i) = 0{*}P[i = 0] + 1{*}P[i = 1] + 2{*}P[i = 2] + \ldots$$

$$E(i) = p/(1 - p)$$

So, for the optimal value of m, the length of the code for $0^{E(i)}1$ should be minimized.

Assume, $E(i) = qm + r$, where $q = floor(E(i)/m)$, and $0 <= r <= m-1$ as modeled in the previous section.

The code of $0^{E(i)}1$ is $1^{E(i)/m}0$(log m bits for r), where $E(i)/m = floor(E(i)/m)$.

The length of the code is: $E(i)/m+1+\log m = p/((1-p)m) + 1 + Ln(m)/Ln(2)$, and is represented as $f(m)$, where, $f(m) = p/((1-p)m) + 1 + Ln(m)/Ln(2)$

To minimize $f(m)$, the derivative $f^d(m)$ should be 0 i.e. $f^d(m)=0$.

$f^d(m) = (1/m) * (1/Ln(2) - p/((1-p)m^2))$

$(1/m) * (1/Ln(2) - p/((1-p)m^2)) = 0$

i.e. $m = Ln(2) * p/(1-p)$

So, for $m < Ln(2) * p/(1-p)$, $f^d(m) < 0$, and for $m > Ln(2) * p/(1-p)$, $f^d(m) > 0$. Thus, at $m = Ln(2) * p/(1-p)$, $f(m)$ achieves an optimal value for the above geometrically distributed data.

## VIII. Performance Measure

To estimate the performance of the proposed algorithm, standard measures like Compression Ratio (CR), Bit Per Pixel (BPP), Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and Execution Time (ET) are considered. CR is the ratio between the original image size and the compressed image size; it can be calculated using equation (6) and (7). BPP is the number of bits that can be used to store one pixel. MSE is the cumulative squared error between the compressed and the original image, PSNR is the measure of the peak error and ET is total time taken by the algorithm to complete the process. MSE is referred to as the distortion between the two images, whereas PSNR is the measure of quality and can be calculated using equation (8) and (9) respectively.

$$CR = N1/N2 \quad (6)$$

(or) $$CR = (N1-N2)/N1*100\% \quad (7)$$

where, N1 is the size of uncompressed image and N2 is the size of compressed image.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[I(i,j) - I'(i,j)]^2 \quad (8)$$

where, $I(i, j)$ is the original image, $I'(i, j)$ is the decompressed image and M, N are the dimensions of the images.

$$PSNR = 10\log_{10}\frac{255^2}{MSE}\,(dB) \quad (9)$$

A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction.

## IX. Experiments and Results

The proposed algorithm has been implemented and tested over more than hundred images at varying bit per pixel from standard benchmark images of different size. Two standard sample image Lena and Mandril which are of size (240 x 240) with pixel values (0-255) are shown in the Fig. 3(a) and 3(b) respectively.

(a) (b)

Fig. 3: Sample Input Image of Size (240 x 240) (a) Lena (b) Mandril

The three level decomposition of wavelet transformation is applied on the input images. The entire image is taken for first level decomposition and at second and third level, only LL subband is taken as described in Section III. The result at each decomposition level for the input image shown in Fig. 3(a) and 3(b) are presented in Fig. 4(a) - 4(f).

(a) (b) (c) (d) (e) (f)

Fig. 4: Result of Wavelet Decomposition for the Original Images Shown in Fig. 3(a) and 3(b). (a) and (b) 1st Level Decomposition, (c) and (d) 2nd Level Decomposition, (e) and (f) 3rd Level Decomposition

In the proposed system, the quantization step size is taken as 2, but it can vary based on the coefficient value and also up to the acceptance level of degradation in the reconstructed image. Thereafter, all the significant bits has been selected at each bit plane to form a context for Golomb-Rice encoder as discussed in Section V and VI. To complete a compression system, the reverse method for each step has been applied. The result of the decompression of sample input images given in Fig. 3(a) and 3(b) are presented in the Fig. 5(a) and 5(b) respectively.

(a) (b)

Fig. 5: Result of Decompressed Images at 0.25 BPP Corresponding to the Original Images Shown in Fig. 3(a) and 3(b) respectively

The decompressed images of JPEG2000 using Embedded Block Coding with Optimized Truncation (EBCOT) and arithmetic coding are given in the Fig. 6(a) and 6(b) for the same sample input images shown in Fig. 3(a) and 3(b) to compare the quality of the decompressed image at same BPP 25.

(a) (b)

Fig. 6: Result of Decompressed Images at 0.25 BPP Corresponding to the Original Images Shown in Fig. 3(a) and 3(b) Respectively Using EBCOT and Arithmetic Coding

The performance of the proposed algorithm has been measured in terms of CR, MSE, PSNR and ET as described in Section VIII. For the input image Lena shown in Fig. 3(a), we could get a value of 92.43, 29.74, and 0.24 respectively for CR, PSNR and ET and for the input image Mandrill shown in Fig. 3(b), we could get a value of 94.21, 30.42 and 0.31 respectively for CR, PSNR and ET. These along with other standard sample images are presented in Table I at different BPP with varying size of image because the performance measures are getting changed with size. In Table II, a comparison of performance PSNR obtained with the proposed scheme and JPEG2000 is presented.

Table I: Results of Performance Measures Obtained with the Proposed Technique

| Input Image | CR (%) | PSNR | BPP | ET (sec) |
|---|---|---|---|---|
| Lena (240 x 240) | 92.43 | 29.74 | 0.25 | 0.24 |
| Mandrill (240 x 240) | 94.21 | 30.42 | 0.25 | 0.31 |
| Lena (256 x 256) | 92.92 | 28.03 | 0.25 | 0.48 |
| Lena (256 x 256) | 96.43 | 25.74 | 0.125 | 0.45 |
| Girl (256 x 256) | 95.82 | 28.93 | 0.125 | 0.38 |
| Lena (512 x 512) | 97.32 | 21.19 | 0.125 | 0.636 |
| Cameraman (512 x 512) | 98.77 | 24.69 | 0.125 | 0.568 |

Table II: Results of PSNR Comparison of Proposed Modified Golomb-Rice (MGR) Coder and JPEG2000 Coder

| 256 x 256 Image (.jpg) | BPP | JPEG2000 | Proposed System |
|---|---|---|---|
| Lena | .1 | 22.48 | 25.27 |
| Lena | .2 | 27.03 | 28.01 |
| Lena | .3 | 28.32 | 28.97 |
| Lena | .4 | 28.98 | 29.18 |
| Mandrill | .1 | 23.19 | 26.46 |
| Mandrill | .2 | 25.58 | 30.13 |
| Mandrill | .3 | 26.07 | 30.46 |
| Mandrill | .4 | 27.21 | 30.87 |

From Table II, it is evident that the proposed coder could provide better results in terms of PSNR than JPEG2000.

## X. Conclusion

In this paper, a modified JPEG2000 compression system has been proposed. The proposed system is based on Golomb-Rice entropy coding. To improve the system performance, mutual relation among bit planes are taken into account and a joint probability based scanning for each bit plane has been performed to select all the significant data. The selected data has been modeled as geometric distribution and formed the context for Golomb-Rice encoding. The proposed technique has been implemented on different size of standard benchmark images and result has been compared with the existing JPEG2000 compression standard in terms of standard performance measures. The proposed method tries to reduce the issues regarding JPEG2000 implementation and gives the better result. This technique can be efficiently implemented in the resource constrained system as it models the binary data and also takes less time to execute.

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