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AN OPTIMIZED BLOCK ESTIMATION BASED IMAGE COMPRESSION AND DECOMPRESSION ALGORITHM

JNVR Swarup Kumar
Assistant Professor, Department of CSE,
Gudlavalleru Engineering College,
Gudlavalleru, India

R Deepika
PG Student, Department of CSE,
Gudlavalleru engineering college, Gudlavalleru, India

ABSTRACT

In this paper, we implemented a new model of image compression and decompression method to search the aimed image based on the robust image block variance estimation. Many methods of image compression have been proposed in the literature to minimize the error rate and compression ratio. For encoding the medium type of images, traditional models use hierarchical scheme that enables the use of upper, left, and lower pixels for the pixel prediction, whereas the conventional raster scan prediction methods use upper and left pixels. In this proposed work, we have implemented block estimation and image distortion rate to optimize the compression ration and to minimize the error rate. Experimental results show that proposed model gives a high compression rate and less rate compared to traditional models.

Key words: Compression, Block Size, Probability, Encode, Decode.

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1. INTRODUCTION

Image compression can be defined [1] in a simple manner as an application of data compression that minimizes the size of the original image without resulting in the degradation of image quality. The principal approach in data compression is the reduction in the amount of image data (the number of bytes) while preserving information (image details). Hence, image compression aims to reduce both the *irrelevance* and the *redundancy* available in the image data with the intention of optimizing and putting to maximum use the data storage and data transmission facilities. Here, the irrelevancy reduction implies that the information removed in this process is systematically selected such that it includes data irrelevant to the user. Such reduction strategy, where the emphasis is on the „meaning‟ of the information, leads to lossy compression. Redundancy reduction, on the other hand, may be employed for lossless compression as it is based on data statistics and leads to the reduction of the reiteration of the same bit patterns in the data. Since image compression addresses the problems of the rate of data transfer (Bandwidth requirements) as well as data storage (Space requirements), its applications and extensive usage are seen in varied fields such as law enforcement, internet applications, medicine, weather predictions, earth resources tracking and management, satellite imagery and countless more. So, in spite of the fast-paced developments taking place regarding superior processing capabilities in terms of the speed of processing, the volume of data storage available and the system performance in general, the ever-expanding needs of the digital media are consistently contributing to the shortage of these facilities. The long strides taken forward due to technological advances still leave space for more development. The demand for better performance is persistent. This situation attests the need for better and better image compression techniques. Hence, there is a need to develop image compression algorithms which ensure improved performance. The performance of image compression algorithms can be measured in terms of metrics such as CR, MSE, PSNR, etc. The improvement in these parameters must also be accompanied by the basic requirement of any application employing compression procedures, i.e., No loss of relevant information and No degeneration in image quality.

The inherent quality of the wavelets can be exploited to meet the diverse and heterogeneous requirements regarding the bandwidth and computational capabilities of individual internet users. In this case, the low end users are provided coarse approximations while the high end users are allowed to utilize maximum bandwidth to meet their fidelity criteria[1-5].

A set of variable-size codes to symbols based on their probabilities. Huffman coding produces ideal variable-size codes (codes whose average size equals the entropy) when the symbols have probabilities of occurrence that are negative powers of 2. This is because the Huffman method assigns a code with an integral number of bits to each symbol in the alphabet.

Raw image and video data bitrate requirements

Picture size (pixels)	Bits per pixel	Frames per second	Bitrate	Common application
800 × 600	24	----	11.52 Mbits	Computer screen images
1600 × 1200	24	----	46.08 Mbits	2 M pixels digital photos
2048 × 1536	24	----	75.49 Mbits	High quality images
320 × 240	12	10	9.22 Mbits / s	Videotelephony
640 × 480	12	5	18.43 Mbits / s	Surveillance
352 × 288	24	30	72.99 Mbits / s	Videoconferencing
720 × 480	24	30	248.83 Mbits / s	Standard TV

Huffman coding is widely used, but is inefficient when the alphabet size is small or symbol probabilities are highly skewed. AVS standard uses a context based lossless coding scheme, namely C-2D-VLC which uses multiple two-dimensional variable length coding tables along with Exponential- Golomb codes to encode symbols. The two-dimensional tables are made adaptive based on contexts [5-7].

2. LITERATURE SURVEY

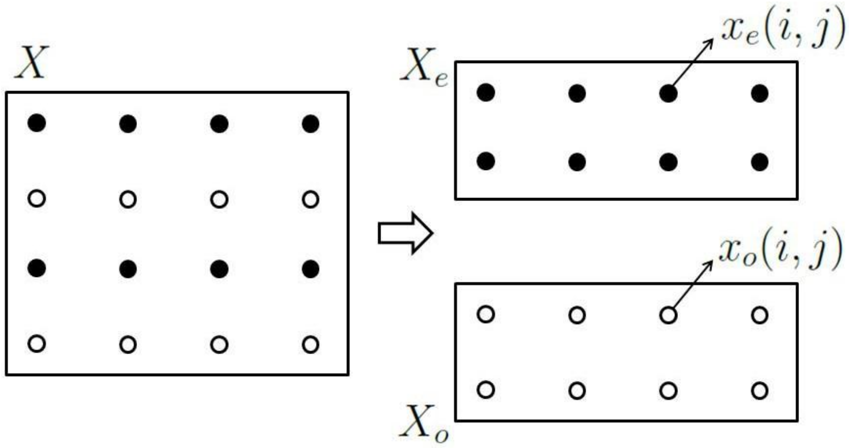
Lossy image compression techniques can be broadly classified into two categories, namely spatial domain techniques and transform domain techniques. In spatial domain techniques, the pixels in the image are used, whereas in transform domain techniques the image pixels are converted into a new set of values, namely transform coefficients, for further processing. Predictive coding is a well known spatial domain technique that operates directly on the image pixels. It consists of three main components, namely quantizer, predictor and entropy coder. The drawback of this technique is that it causes more blurring of image edges and distortions in smoother areas. Also, the design process is complex in the sense that the predictor must be designed assuming zero quantization error and quantizer must be designed to reduce its own error. Transform coding is a widely used method in lossy image compression. An image is compressed by transforming the correlated pixels to a new representation (transform domain) where they are decorrelated, that is, the transform coefficients are independent of one another and most of the energy is packed in a few coefficients. The transform coefficients are quantized to reduce the precision of these values so that very few quantized nonzero coefficients have to be encoded. This is a many-to-one mapping, and consequently a lossy process, which provides the main source of compression. Quantized coefficients are further compressed using entropy coding techniques to provide a better overall compression. The transform used is a linear transform so that the task of compressing in the transform domain is more efficient and simple. There are many hybrid image compression techniques that are based on DWT and JPEG standard The wavelet coefficients in each subband are JPEG coded in different ways. In [4] the input image is first transformed by Discrete Cosine Transform (DCT) and the lowest frequency components are split into sixteen fine uniform subbands by considering correlation and energy in the frame. This algorithm offers high CR and good subjective quality compared to JPEG standard for any specified value of PSNR. The Log-Exp image compression algorithm operates pixel-by-pixel without producing any blocking effects as in JPEG standard. This algorithm uses Huffman coding technique which is a static technique and consumes more time. Also, Huffman coding is inefficient when the symbol probabilities are highly skewed. Block Truncation Coding (BTC) techniques are known for their speed and reduced computational complexity since complicated transforms are not used The principle used in BTC algorithm is to use two-level quantizer on each non-overlapping 4 BY 4 blocks of the image. The quantizer adapts to local properties of the image while preserving the first- or first- and second-order statistical moments. The BTC technique of Delp preserves the first- and second-order moments. In the Modified BTC (MBTC) of Udpikar (Udpikar and Raina 1987), only the first-order moments are preserved. The parameters transmitted or stored in the BTC based algorithms are the statistical moments and the bitplane. The BTC techniques yield good quality images at a bitrate of 2 bpp or a CR of 4. [8] have proposed “an interpolative coding approach using JPEG technology with the aim of reducing the visually unpleasant blocking artifacts produced by JPEG at low bit rates” or higher compression levels. When compared with JPEG, this scheme has achieved higher PSNR at low bit rates.

Bruckstein, Elad and Kimmel have also worked in the same direction in order to improve on the objective as well as the subjective performance of JPEG. They have employed a down sampling approach based on image statistics, size and the available bit budget, prior to JPEG coding. This approach has several advantages. Since the down sampling is done prior to coding, the computational complexity in the coder/decoder is decreased significantly. The visual quality and the PSNR performance are also enhanced considerably. Also, this approach allows an expansion in the range of the employable bit-rates in compressing the image satisfactorily. However, this work is limited in that it uses fixed filters for decimation and interpolation. Inspired by the above work, Tsaig et al. have improved upon it by introducing optimal filters for decimation along with interpolation stages, thereby achieving significant gain in both qualitative and quantitative metrics. Though all these schemes have good proposals, they are limited in the under stated aspects: a) The down sampling ratio is fixed by the user; b)the critical bit rate is low and is imagedependent; c)the encoder has to switch between a down sampling scheme and traditional scheme to give a good coding quality for different images[8-11].

3. PROPOSED WORK

Traditional Model Image Decomposition

For more accurate prediction of these signals, and also for accurate modeling of the prediction errors, we use the hierarchical scheme: the chrominance image is decomposed into two subimages; i.e. a set of even numbered rows and a set of odd numbered rows respectively. Once the even row subimage X_e is encoded, we can use all the pixels in X_e for the prediction of a pixel in the odd row subimage X_o. In addition, since the statistical properties of two subimages are not much different, the pdf of prediction errors of a subimage can be accurately mod- eled from the other one, which contributes to better context modeling for arithmetic coding as shown in Fig.



For the efficient compression, the statistics of symbols (prediction errors) should well be described by an appropriate model and/or parameters. Traditional model used the prediction error as a random variable with pdf $P(e|C_n)$, where C_n is the coding context that reflects the magnitude of edges and textures. Specifically, C_n is the level of quantization steps of pixel activity $\sigma(i, j)$ defined as

$$\sigma(i, j) = |x_e(i, j) - x_e(i + 1, j)|.$$

Proposed Model Modification

Step 1: Read Color Image.

Step 2: RGB is first transformed to YCuCv.

$$\begin{bmatrix} D \\ E \\ F \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \frac{1}{256}\begin{bmatrix} t_{11} & t_{12} & t_{13} \\ t_{21} & t_{22} & t_{23} \\ t_{31} & t_{32} & t_{33} \end{bmatrix}\begin{bmatrix} R \\ G \\ B \end{bmatrix},$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \frac{1}{256}\begin{bmatrix} s_{11} & s_{12} & s_{13} \\ s_{21} & s_{22} & s_{23} \\ s_{31} & s_{32} & s_{33} \end{bmatrix}\begin{bmatrix} D-c_1 \\ E-c_2 \\ F-c_3 \end{bmatrix},$$

where mostly $c_1 = c_2 = c_3 = 0$. Nevertheless for the YC_BC_R color space, there is $D = Y$, $E = C_B$, $F = C_R$ and $c_1 = 16$, $c_2 = c_3 = 128$

Step 3: Image RGB components transformation

Step 4: for each block size NXN.

Find the block variance

$$\bar{x} = \frac{1}{N^2}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} x(i,j)$$

$$\sigma = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} | x(i,j) - \bar{x} |$$

Step 5: Each block is estimated from the previous frame using Sum of absolute difference.

$$SAD(\min) = \min \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} | \mathrm{x(i,\,j)} - Cummprob(x(i,j))(i-1, j+1) | \quad Cummprob =$$

$$0.5 * \pi(x(i,j) - median) / scale$$

Step 6:

dev = x - median;

Density= (1 / PI) * (scale / (dev * dev + scale * scale));

Step 7: After the color transformation, the luminance channel *Y* is compressed by a JPEG-LS coder. Pixels in chrominance channels are predicted by the traditional hierarchical decomposition and directional prediction.

Step 8: Calculate the distortion measure, according to the following formula

$$D = \sum_{i,j=0}^{N} (\bar{p} - p)^2$$

Finally, an appropriate context modeling of prediction residuals is introduced and arithmetic coding is applied.

4. EXPERIMENTAL RESULTS

All experiments are performed with the configurations Intel(R) Core(TM)2 CPU 2.13GHz, 2 GB RAM, and the operating system platform is Microsoft Windows XP Professional (SP2).

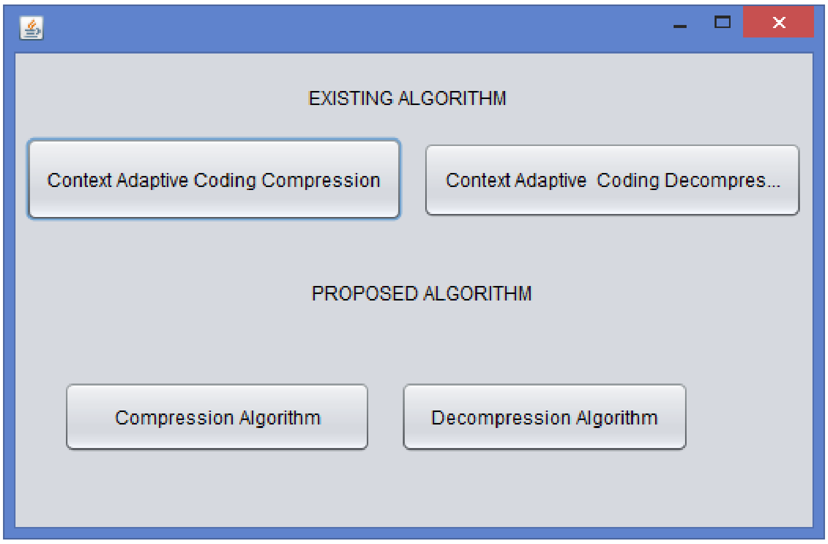


Figure 1 Home view of Proposed Approach

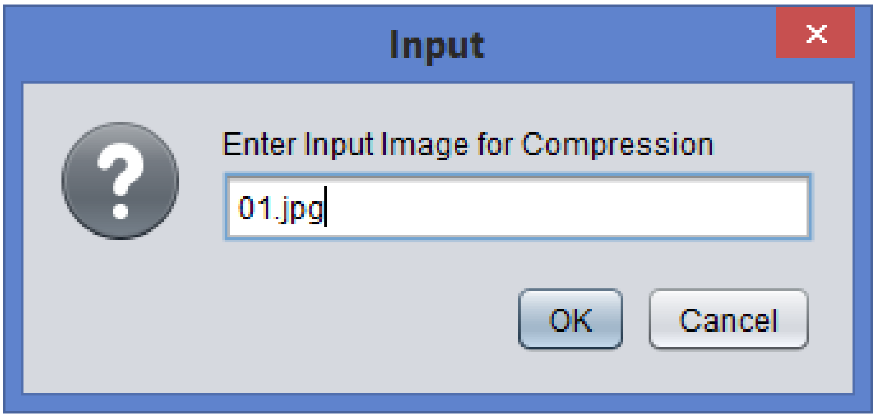


Figure 2 Input image

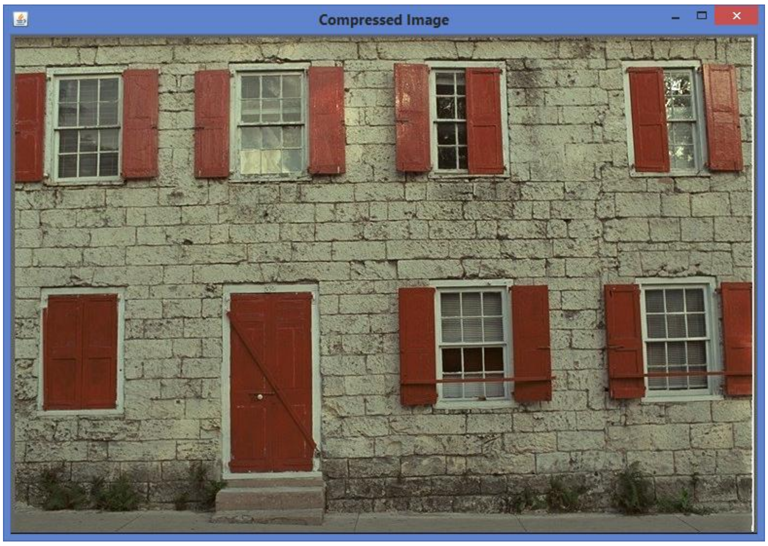
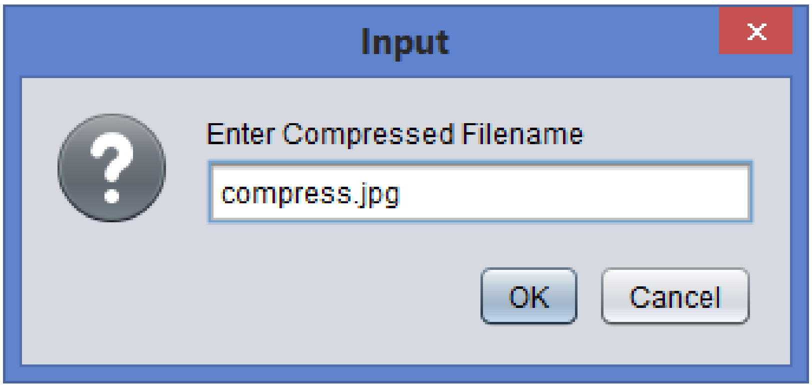
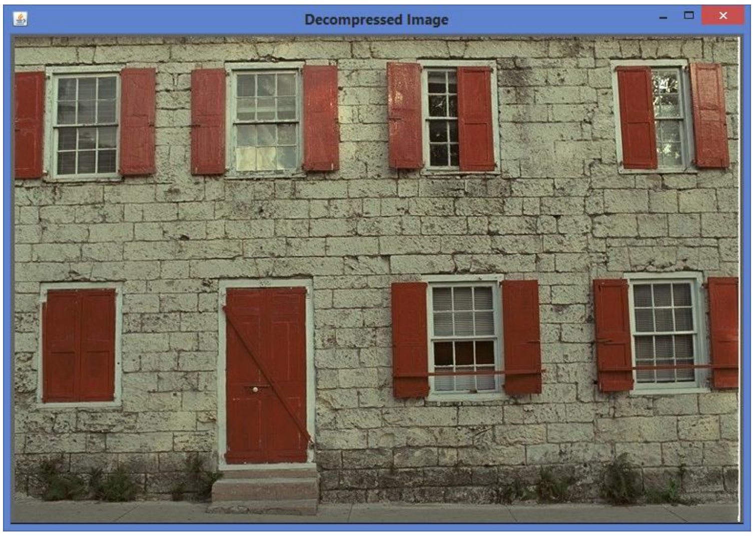


Figure 3 Existing Compression Model

Compressed Bit Rate (CBB): 14.97587
Compressed Time: 0.89881
PSNR RATIO: 0.96389
MSE: 0.28049

Decompression





Proposed Model Compression Results

Compressed Bit Rate (CBB): 9.28099
Compressed Time: 0.71977

Image Size (KB)	Existing Model Compression Rate (%)	Proposed Model Compression Rate (%)
15	14.56	8.95
20	15.34	9.76
30	18.25	11.56

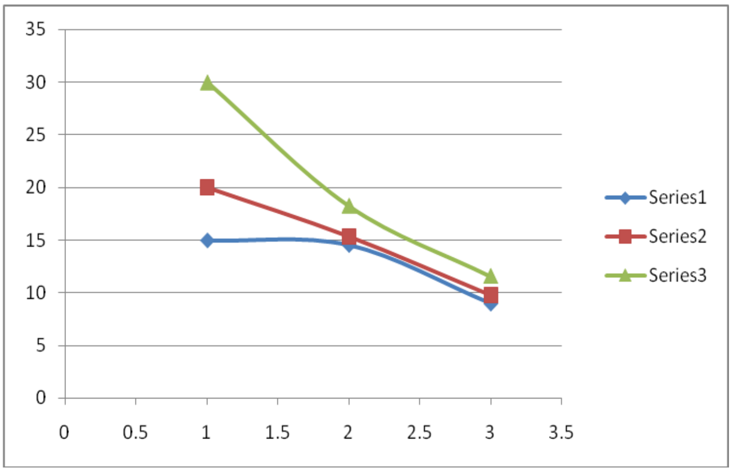
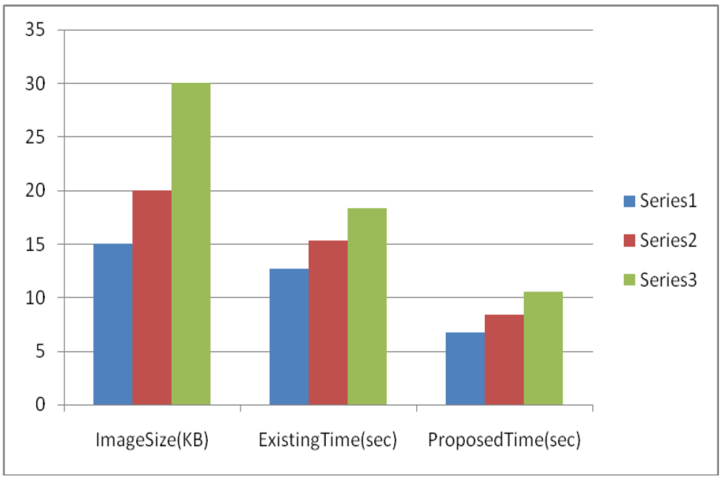


Image Size (KB)	Existing Time (sec)	Proposed Time (sec)
15	12.67	6.78
20	15.34	8.45
30	18.34	10.56



CONCLUSION

Propoed model compress high dimensional images with high compression rate and less distortion rate. For encoding the medium type of images, traditional models use hierarchical scheme that enables the use of upper, left, and lower pixels for the pixel prediction, whereas the conventional raster scan prediction methods use upper and left pixels. In this proposed work, we have implemented block estimation and image distortion rate to optimize the compression ration and to minimize the error rate. Experimental results show that proposed model gives a high compression rate and less rate compared to traditional models.

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