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Research Article

Predictive Coding Based Lossless Image Compression Model

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Received: 06 June 2022; Revised: 28 June 2022; Accepted: 29 July 2022; Published: 07 October 2022
AID: 0001-02-000012

Abstract: Image compression is a procedural technique wherein images undergo compression by means of encoding image data using fewer bits and eliminating redundant information. Prior to storage or transmission via a communication medium or network, image data undergoes compression. Various methods are employed for the encoding and decoding of images within the digital image compression process. Due to the critical nature of medical and military image data, the most obvious choice is a lossless compression technique. The predictive coding method consists of prediction, context modelling, and entropy coding. Since current predictors don't work efficiently for different types of images due to their performance limitations in different portions of the image, to overcome this problem, the research target is to develop a context-sensitive method by clustering the input image. And calculate the context of pixels by calculating the 20-dimensional difference vector. Update the weights of clusters after calculating the prediction errors of each pixel. Finally, by applying Golomb coding after updating the cluster's weights, the output stream image is compressed with fewer bits. The proposed method obtains a relatively higher compression ratio for continuous-tone images than other lossless predictive coding techniques. The proposed method reduces the compressed stream size by 13%. This is a significant improvement in storing images with fewer bits after compression.

Keywords: Predictive coding; Lossless compression; Clustering; Context sensitive prediction

1. Introduction

In digital image processing, image compression is a method in which images are encoded with fewer bits by removing redundant data prior to storage over a network and then inserted again during the related process of decompression. Image compression is a tool which is cost effective for maintaining the expensive resources, i.e. communication bandwidth and data storage space. Image compression can be in the form of lossless (LS) or lossy compression [19]. In lossless compression input message is equivalent to the output message. When the file is uncompressed with lossless compression, each bit of data which was initially in the file remains unchanged and the whole information is restored. Development of more efficient and lossless compression techniques for images is a major topic for future research and has many potential applications such as military and medical imaging. Early methods of LS were Run-length encoding [1], Entropy encoding [2], Adaptive dictionary algorithms such as Lempel–Ziv–Welch (LZW) [3] and Predictive coding [20] are different lossless compression techniques.

In Lossless Predictive coding, Predictive coding method mainly depends on a predictor, context model and entropy coding [4]. Predictor is the basic phase at which large amount of spatial redundancy is eliminated. Gradient Adjusted Predictor (GAP) [10] that is used in CALIC and in JPEG_LS [8], Median Edge Detector (MED) predictor [11], is the most well-known predictors. Predictive method that consists of a gradient adjusted predictor (GAP) is based on least mean square adaptation of linear predictive coefficients [5]. The adaptation is based on connecting neighbor pixels, so intensity value of each pixel will be predicted with an optimal predictor. And median edge detection (MED) predictor based on static predictor. The static predictor is mostly a switching predictor which is capable to adapt context of numerous types, such as smooth area, vertical edge or horizontal edge [6]. JPEG-LS, an efficient compression standard for continuous tone images used near-lossless or lossless mechanism, which was developed in order to offer a low complexity compression standard which provides improved compression proficiency as compared to lossless JPEG. JPEG-LS will attain better decorrelation. By using JPEG-LS, compression is usually much faster than that of JPEG 2000 [7].

This research presents a new context-based method. Context based method will only estimate prediction error's expectation with perspective of context of pixels instead of estimating conditional errors probabilities. Technique for prediction error estimation can handle a large quantity of contexts modeling. The low space and time complexities can be achieved by using effective methods for making, quantizing and modeling contexts. Proposed method will obtain relatively high compression ratio of continuous-tone images than with other lossless predictive coding techniques.

This paper presents some background knowledge about the predictive lossless compression in section 2. And proposed context sensitive method for lossless compression is discussed in section 3. Implementation of proposed method and its experimental results are presented in section 4, and sections 5 concludes research.

2. LITERATURE REVIEW

LOCO-I (Low Complexity Compression for Images) is a fundamental algorithm at the heart of the new ISO/ITU standard for lossless and near-lossless compression of continuous-tone images [8]. This method achieves the benefits of both simplicity and the compression potential of context models. LOCO-I employs a straightforward fixed context model that comes close to the capabilities of more intricate universal techniques for capturing high-order dependencies. The key strengths of LOCO-I lie in its ability to achieve compression ratios that are either comparable to or surpassing those obtained with cutting-edge schemes utilizing arithmetic coding.

Li and Orchard [9] demonstrate the effectiveness of LS-based adaptation schemes for lossless compression of natural images. They present a method for reducing computational complexity that involves updating predictor coefficients only when the amount of the prediction error rises above a chosen threshold. This update process is performed on an edge-by-edge basis, eliminating the need for pixel-by-pixel LS optimization while still delivering the benefits of LS-based adaptation.

In an alternative image compression method, Tiwari and Kumar [10] concentrate on enhancing the prediction accuracy of the Gradient Adjusted Predictor (GAP) used in CALIC. They aim to achieve this improvement with only a marginal increase in computational complexity. Their approach employs the Least Squares (LS) method to determine optimal predictors for pixels belonging to various slope bins within GAP. These selected predictors, after quantization, are utilized for both encoding and decoding predictions. The approach identifies all pixels belonging to a specific slope bin of GAP. A notable advantage of this method is its computationally simpler encoder. GAP can find utility in the compression of medical images.

Avramovic and Reljin [12] introduce the Gradient Edge Detection (GED) predictor, which harnesses the strengths of the previously described MED [11] and GAP predictors. GED is a fusion of these two techniques and employs five neighboring pixels to estimate the local gradient and predict the current pixel's intensity value. This approach strikes a balance between MED's use of three neighbor pixels and GAP's reliance on seven. The GED method is remarkably simple while being based on the GAP predictor mechanism. GED is significantly more streamlined than GAP, yet it produces bit rates that are just 1% higher.

In a different technique, Gang et al. [13] propose a novel lossless compression method that combines JPEGLS with motion estimation. By adding motion vectors into the JPEG-LS framework, this method improves compression performance, outperforming JPEG-LS on its own. Notably, this method outperforms both JPEG-LS and JPEG2000 [14].

Huang and Rao [15] delve into predictive coding as a unifying framework for understanding redundancy reduction and efficient coding in the nervous system. By conveying just, the unexpected sections of sensory inputs, predictive coding enables the nervous system to minimize redundant information and maximize neuron dynamic range.

Valova, I., and Y. Kosugi [16], develop a comprehensive algorithm for the decomposition and compression of grayscale images. This approach expresses decomposition as a functional relation between the original image and Hadamard waveforms. The dynamic adaptive clustering procedure incorporates potential functions as a similarity measure for clustering and includes a re-clustering phase. The effectiveness of this technique depends on how easily it can compress grayscale photos.

Kattan [17] explores data compression algorithms and proposes the GP zip family (GP-zip, GP-zip*, GP-zip2, and GPzip3) as a series of intelligent universal compression systems. These systems are designed to combine well-known data compression techniques in order to create a flexible data compression solution that can successfully handle a variety of data types, especially archive files.

In their work, Tiwari and Kumar [18] introduce a collection of statistically valid sixth-order predictors tailored for seven distinct classes of pixels. Their technique involves categorizing pixels based on the seven slope categories within the Gradient Adjusted Predictor (GAP) framework, making this set of predictors applicable within the context of GAP.

Dong, Wu, et al. [21] propose a context-based adaptive image resolution up-conversion approach, placing significant emphasis on modeling image data. Compared to other methods for lossless image coding reported in the literature, their codec delivers superior lossless compression of continuous-tone images.

J. Rigau et al. [22] introduce a novel method for assessing the complexity of an image. Depending on the framework employed, this approach elucidates the information flow from the image histogram to partitioned sectors of the image under consideration.

Barowsky et. al. [23] explores efficient lossless dataset compression algorithms, crucial for reducing storage and transmission bandwidth in diverse applications. The theoretical framework, based on permutation-invariant structures, provides new opportunities for code design. The study introduces a predictive coding scheme for image dataset compression, showcasing superior performance over benchmarks like xz and JPEG-LS on MNIST and CIFAR-10.

Latha et. all [24] addresses the critical issue of managing memory and communication costs associated with storing and transmitting Dicom images in the healthcare domain. The article uses wavelet transform, Lifting Scheme, Linear Predictive Coding, and Huffman Coding for Dicom picture reduction, introducing a novel technique.

3. PROPOSED METHOD:

Lossless predictive coding primarily relies upon three key components: a predictor, a context model, and entropy coding. Among these components, the predictor assumes paramount significance as it plays a central role in the elimination of spatial redundancy. In this research, image is processed by making different clusters of the input image. Clusters of pixels are formed with the assistance of a difference vector. To calculate the local context of a pixel, find the belonging cluster of pixel by calculating the 20Dimensional difference vector and calculate the neighbors of current pixel X as shown in table 1. Apply context sensitive prediction mechanism and calculate the prediction error e_A and e_B of current pixel with respect to neighbors A and B using equation 2 and 3 respectively. And apply Golomb coding on it after updating weights of each cluster by using equation 6. Final output is the compressed stream of image after compression. Context of a pixel is given in figure 1.

		X_N	X_O	X_P		
	X_M	X_G	X_H	X_I	X_Q	
X_L	X_F	X_C	X_B	X_D	X_J	X_R
X_K	X_E	X_A	X			

Figure 1: Context of pixel

The algorithm developed on the basis of this context a clustering algorithm is used to define 'prediction-contexts'. After clustering, each cluster will represent a 'prediction-context'. The proposed algorithm is given as under and after that flow diagram of research is presented in figure 2.

3.1. Algorithm:

1. Take an image.
2. Select and make clusters of the pixels based on the difference vector as defined in equation.

$$D_V = [X_A - X_C, X_C - X_B, X_E - X_D, X_A - X_E, X_B - X_H, S_F * X_A]$$

3. For each pixel of the image.
   a. Find the belonging cluster of pixels by calculating 20-dimensional difference vector of the context. This is called local context of pixels.
   b. Calculate neighbors (A, B, C) of the pixel X.
   c. Apply context sensitive prediction mechanism.
   d. Calculate prediction error e_A and e_B of the image with respect to its neighbors.
   e. Update weights of each cluster.
4. Apply Golomb coding after updating of each cluster's weight.
5. Output a compressed stream of the image.

3.2. Flow Diagram:

The flowchart outlines the process of image compression using Golomb coding. It begins with an input image, applies K-means clustering, and uses a predictor to calculate pixel values. The prediction error is then encoded using Golomb coding, resulting in a compressed output stream.

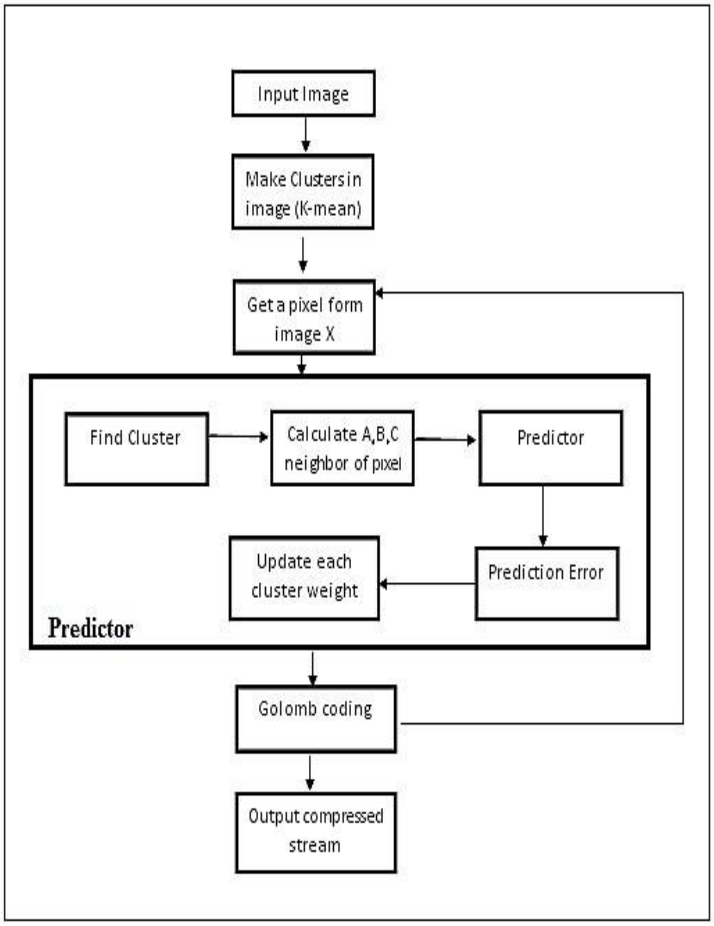

Figure 2: Flow diagram of context-based method

Description of context sensitive method is as follows:

3.2.1. Context of a pixel X

Take a 64-Bit image, and then crop this image by eliminating 3 corner rows and 6 columns. Now use the cropped image to make clusters.

$$No. of\ Clusters\ (N_C) = \frac{sqrt(width * height)}{10}$$

Then calculate the number of training samples, selected randomly from the image.

No. of training samples = $S_N = 500 * N_C$

(selected randomly from the image)

3.2.2. Difference Vector

To randomly choose a set of training samples, denoted as 'Sn', from a cropped image, we randomly select index numbers from a set denoted as 'p'. These selected index numbers are used to obtain the difference vector from the corresponding pixels in the uncropped image.

The difference vector for each randomly selected pixel is defined by equation no. 1:

$$D_V = [X_A - X_C, X_C - X_B, X_E - X_D, X_A - X_E, X_B - X_H, S_F * X_A] \quad (1)$$

Where S_F= Scaling Factor and $X_{A, B, C, D, E, H}$ are position of pixels.

3.2.3. A pixel's local context

The image is now ready for prediction.

Now the image is ready for the prediction. Firstly, 6-Dimensional Difference Vector to find the current pixel prediction, context (cluster). To find current pixel prediction, context (Cluster), find the distance from all clusters. After getting the cluster index of the current pixel, calculate an index of minimum distance for each Dv. Then find 20Dimensional Difference Vector di. The 20-Dimensional Difference vector di local context of current pixel is shown in Table 1.

Table 1: Local context of Current pixel

$D_1 = X_A - X_C$	$D_{11} = X_H\ X_0$
$D_2 = X_C - X_B$	$D_{12} = X_F - X_M$
$D_3 = X_B - X_D$	$D_{13} = X_K - X_L$
$D_4 = X_A - X_E$	$D_{14} = X_O - X_N$
$D_5 = X_B - X_H$	$D_{15} = X_J - X_Q$
$D_6 = X_C - X_G$	$D_{16} = X_J - X_R$
$D_7 = X_E - X_F$	$D_{17} = X_C - X_F$
$D_8 = X_D - X_I$	$D_{18} = X_I - X_P$
$D_9 = X_D - X_J$	$D_{19} = X_H - X_I$
$D_{10} = X_E - X_K$	$D_{20} = X_H - X_G$

3.2.4. Prediction Error of a pixel from its neighbor A:

Equation 2, e_A prediction error for current pixel according to neighbor A is calculated:

$$e_A = X - X'_A \tag{2}$$

3.2.5. Prediction Error of a pixel from its neighbor B:

e_B prediction error for current pixel according to neighbor B is shown in equation 3.

$$e_B = X - X'_B \tag{3}$$

3.2.6. Prediction using weights of the Context of a pixel with respect to neighbor A:

Initialize cluster weights to zero. Then update weights of the cluster of the current pixel after every prediction by using the equation 4.

$$X'_A = A \sum_{i=1}^{20} Wi[PX]di \tag{4}$$

3.2.7. Prediction using weights of the Context of a pixel with respect to neighbor B:

Initialize weights to zero. Then update weights of the cluster of the current pixel after every prediction as shown in equation 5 and 6

$$X'_B = B \sum_{i=1}^{20} Wi[PX]di \tag{5}$$

3.2.8. Weights updating:

$$\omega i = \omega i + \mu i \,.\, e'.\frac{di}{|di|+1} \tag{6}$$

3.2.9. Learning Rate:

Initialize learning rates by using equation 7.

$$\mu i = \begin{cases} 4/10000 & for\ i \leftarrow \{1,2,3\} \\ 2/10000 & for\ i \leftarrow \{4,5\} \\ 1/10000 & for\ i \leftarrow \{6,7 \ldots 20\} \end{cases} \tag{7}$$

3.2.10. Threshold for error:

e_A all prediction errors of pixels of cluster

$$e' = sign(e_A).min\ (|e_A|, th[px]) \tag{8}$$

e_B all prediction errors of pixels of cluster

$$e' = sign(e_B).min\ (|e_B|, th[px]) \tag{9}$$

According to neighbors A and B, the threshold for errors is depicted in equations 8 and 9, respectively.

$$\overline{|di|}\ [px] = \overline{|di|}[px].7 + {|di|}/{8} \tag{10}$$

4. EXPERIMENTS

4.1. Dataset:

The compression algorithm is tested using three different categories of data sets as shown in figure 3. The data set consist of Lena, Barbara, airplane, Baboon, Barb2, Boat1, Boat2, Cameraman, Clown, Couple, Gledhill, Man, Monarch, Peppers, and Balloon with 64 x 64 dimensions, 128 x 128 dimensions and 256 x 256 dimensions. It is a mixture of grayscale images and color images. A 64 x 64 dimensions dataset is shown in figure 3.

Figure 3: Data Set images

4.2. Results:

After applying JPEG-LS method on given data set, prediction error of dataset Lena, Barbara, airplane, Baboon, Barb2, Boat1, Boat2, Cameraman, Clown, Couple, Gledhill, Man, Monarch, Peppers, and Balloon, are presented in figure 4.

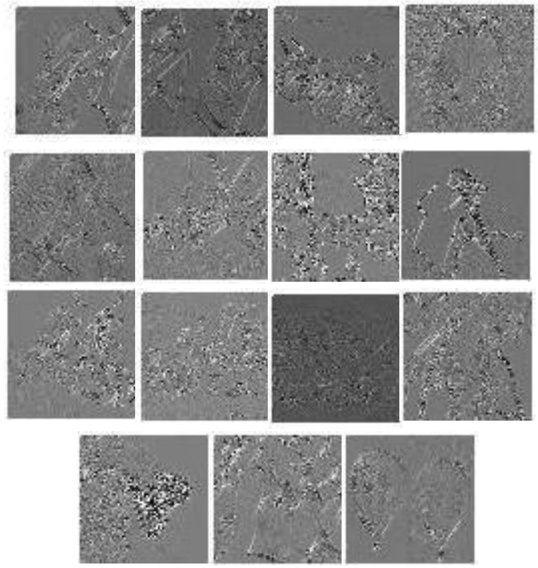

Figure 4: Prediction error after JPEG-LS predictor implementation

And after applying proposed context-based method on given data set, prediction error of dataset Lena, Barbara, airplane, Baboon, Barb2, Boat1, Boat2, Cameraman, Clown, Couple, Gledhill, Man, Monarch, Peppers, and Balloon, are shown in figure 5.

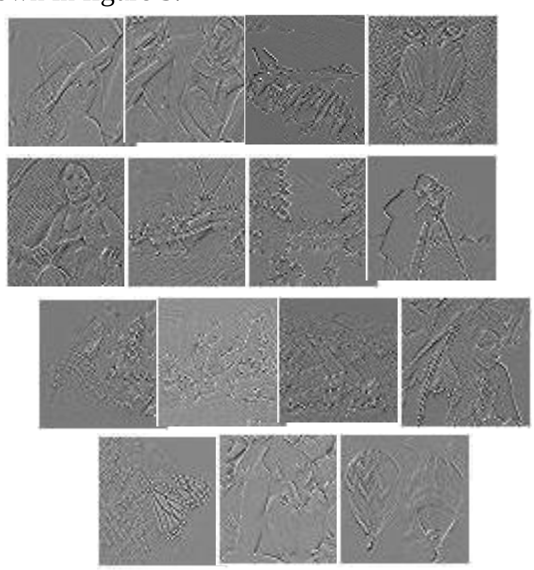

Figure 5: Prediction error after proposed context-based predictor implementation

In this research, proposed context-based method takes less bits to store the image after compression as compared to JPEG-LS method. This is a significant improvement to store images with lesser bits after compression. Resulting less utilization of storage space and bandwidth to transfer images over a network.

4.3 Comparison:

In this research, proposed context-based method is compared with JPEG-LS [13]. There is less number of bits required to store information after image compression using proposed method as compared to JPEG-LS method. Experimental results are presented with the help of column chart to illustrate the difference as shown in figure 6 for 64x64 image date set, figure 7 for 128x128 images data set and in figure 8 for 256x256 image data set.

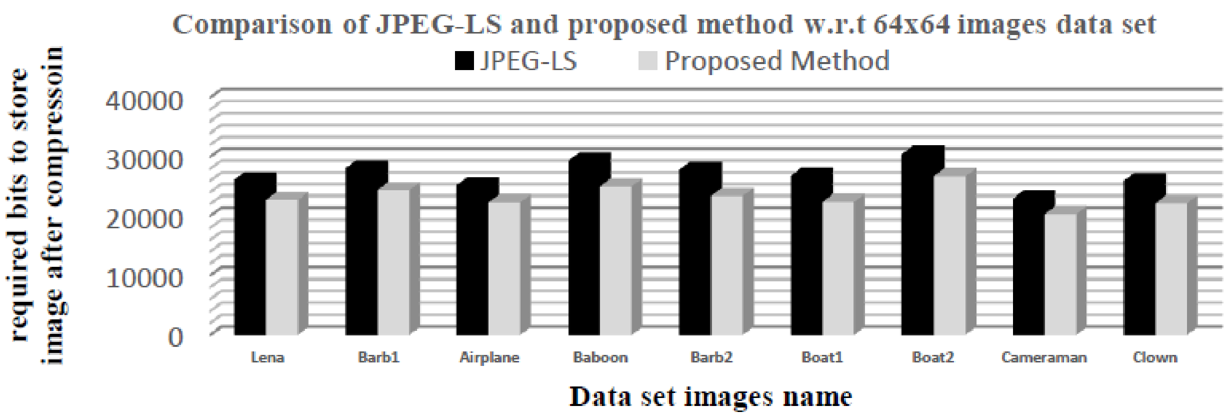

Figure 6: Comparison of JPEG-LS and proposed method w.r.t 64x64 images data set

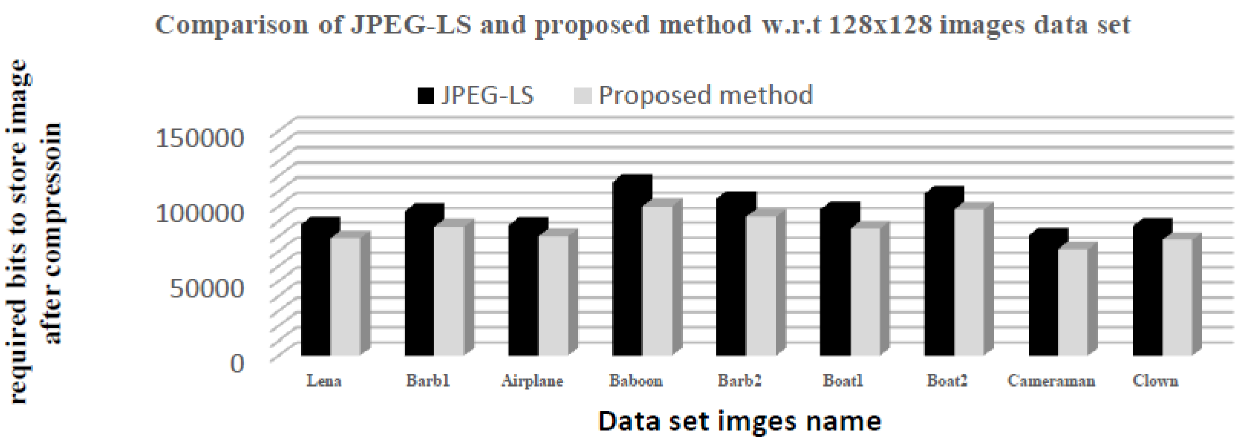

Figure 7: Comparison of JPEG-LS and proposed method w.r.t 128x128 images data set

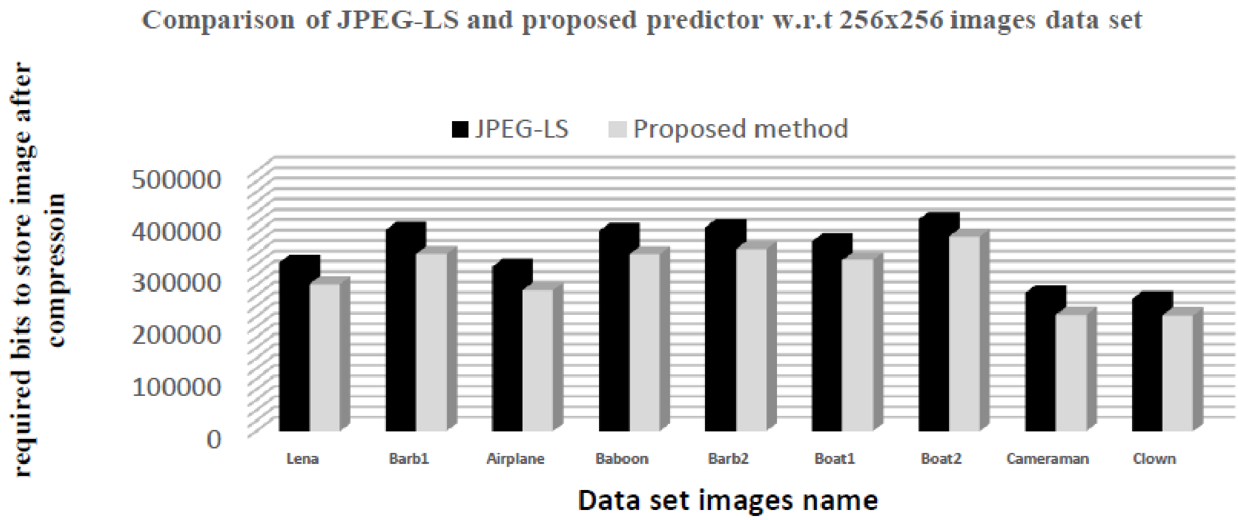

Figure 8: Comparison of JPEG-LS and proposed method w.r.t 256x256 images data set

5. CONCLUSION:

In this study, a context-based, lossless picture compression method called predictive coding is suggested. The experimental findings demonstrate that the proposed technique outperforms JPEG-LS. After compression of different images data set w.r.t three different dimensions of image resolution, context sensitive method is compared with JPEG LS method. Proposed method reduces the compressed stream size by 13%. This is a significant improvement to store images with fewer bits after compression.

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