Lossless Grayscale Image Compression using Block-wise Entropy Shannon (LBES)

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ABSTRACT
This research paper based on the probability based block wise Shanon Entropy method applied in grayscale image based on frequency occurrence of each pixel value. Then the LBES method divide the pixel with frequency of each set as assigned either 0 or 1 coding. This successful compression algorithm for utilizing optimum source coding. This theoretical idea can be proved in a range of , where H is the entropy of the source. The main Analysis of this paper is to show the better compression with other Lossless methods, with the proposed algorithm Lossless Block-wise Entropy Shannon (LBES) is suitable for produce high compression ratio 19.54 compared to other standard methods. Compression ratio is determined for all sub blocks. This process repeats for all components wise. The proposed Lossless Block-wise Entropy Shannon (LBES) is tested and implemented through quality measurement parameters such as RMSE, Entrropy, PSNR and CR by using MATLAB..

General Terms
Lossless image compression, Shannon Entropy

Keywords
Compression, Decompression, Entropy, MSE and PSNR.

1. INTRODUCTION
A digital image is a row and column array of dots, or picture elements, classified in m rows and n columns. The expression $m \times n$ is specifies the resolution of the image, and the dots are called pixels (exclude in the cases of fax images and video compression, it is referred to as pels). The term “resolution” is constantly used to further illustrate the number of pixels per unit length of the image.

Data compression is the key techniques, enabling technologies for multimedia applications. It hasn't resolved to be practical images, audio and video on websites if do not use data compression algorithms. Mobile phones are not able to produce communication clearly after data compression. With data compression techniques, it can compress the loss of resources, such as hard disk space or transmission bandwidth.

One way of segregating the compression schemes is by used to represent the redundancy. However, more popularly, compression schemes are divided into two main groups: lossless compression and lossy compression. Lossless compression preserves all the information in the data being compressed, and the reconstruction is identical to the original data [1].

Images are transmitted over the World Wide Web an excellent example. Suppose it need to download a digitized color photograph over a computer’s 33.6 kbps modem. If the image not compressed (a TIFF file, for example), it will contain about 600 kbytes of data. If Lossy compression using a Lossless technique (such as used in GIF format) it will be about the one-half the size , or 300 kbytes. If Lossy compression has been used (a JPEG file), it will be about 50 kbytes. The point is , the download times for these three equivalent files are 142 seconds, 71 seconds and 12 seconds respectively [2] .

In this research paper, the researchers are going to design an image-independent Lossless probability Entropy Shannon Algorithm which can be used for both display and grayscale image processing [3].

This paper is organized as follows, Section 1 presents the basic introduction of compression and its types. In Section 2, reveals the literature review of the Lossless image compression Section 3 Shannon Fannon Entropy Representation Section 4 Provides the Proposed method .Section 5 discusses the experimental results with comparison of different compression LBES grayscale images. The conclusion and future direction, are discussed in Section 6 and Section 7.

2. LITERATURE REVIEW
The main issues, of digital images, how to stores data and convey a digital image has been a case of research for more than 40 years and it was originally consumed by military applications and NASA. The problem is simply notified and it is, How does one efficiently represent an image in binary form? This is the image compression problem. It is a special case of the source coding problem addressed by Shannon in his landmark paper [4] on communication systems.

The image compression is framed under the general umbrella of data compression, which has been studied theoretically in the field of information theory [5], pioneered by Claude Shannon [6] in 1948. Information theory sets the basics constrained in compression performance theoretically feasible for convincing classes of sources. This is very effective because, it gives a theoretical benchmark against which one can compare the performance of more practical but suboptimal coding algorithms.

Historically, the lossless compression issues came first. The goal is to compress the source of data with no loss of information. Shannon provides that given any discrete source with a well structured statistical method (i.e., a probability mass function), there is a fundamental theoretical restriction to can compress the source before it start the loss of information. This limit is called the entropy of the source. In many terms, entropy assigns to the ambiguity of the source.

For example, the source, proceeds on each of N discrete values of al, a2, . . . , uN with equal countable values has an entropy given by log, N bits per source symbol. If the symbols are not equally likely, however, then it provides better performance because more predictable symbols should be assigned fewer bits. The basic limit is the Shannon entropy of the source.

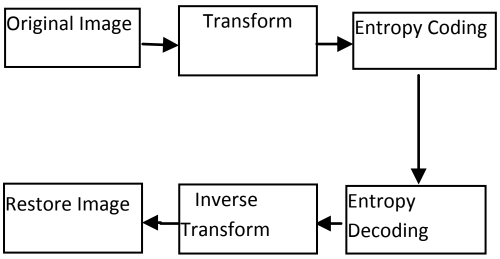

Fig 1: Lossless Image Compression

In this review Lossless compression technique is proposed to classify to obtain compression at high ratio (Figure 1). As the characteristics of image exploited local and global redundancy so it decrease redundancy at both local and global levels. First separated the image into blocks of distinct length and then counting on the characteristics of pixels in each block encode these pixels. The technique provides more competence with respect to other Lossless algorithms and well result is achieved [7].

The standard approach in compression is to describe the classes of sources, constructing different types of data. The paper adopt that the data are produced by a source of some selection and apply a compression method designed for this discriminating class. The algorithms working well on the data that can be estimated as an output. [8] Before it retraction to the relations of universal Lossless data compression algorithms, the paper have to indicate the entropy coders.

An entropy coder is a method that allocates to every symbol from the alphabet a code susceptible on the probability of symbol existence. The symbols that are increase possible to be present get shorter codes than the less probable ones. The codes are consigned to the symbols in such a way that the predictable length of the compressed success is minimal. Approximately the common entropy coders are Huffman coder and an arithmetic coder. Both the methods are indefectible, so anyone cannot allot codes for which the established compressed sequence length would be shorter. The Huffman coder is excellent in the class of methods that allocate codes of integer length, while the arithmetic coder is free from this limitation. Therefore, it usually leads to shorter expected code length [9].

The main idea in image compression is to decrease the data stored in the original image to a smaller amount. Comparable to the scientific revolution in the internet and the elaboration of multimedia applications, the requirements of the modern technologies have been developed. In recent times, many different methods have been well-established to acknowledge these essential for both Lossy and Lossless compression [10][11].

Therefore, our proposed method which is called Lossless Block-wise Entropy Shannon (LBES) is consists of dividing the image into blocks of 8×8 pixels each. Obviously, the proposed method knows that each pixel is a number between 0 to 255. Therefore, if the method can transform each pixel value to assign a code word length to calculate the Entropy value for better compression ratio in Lossless image compression.

From the above literature survey, the existing method of Lossless compression is not sufficient to get more compression ratio as well as image quality. To overcome the above said problem, it needs to develop and design a new proposal Block-wise Entropy Shannon Techinque Lossless compression algorithm for grayscale images.

3. SHANNON ENTROPY REPRESENTATION

A Shannon-Fano tree is made according to the blueprint of design effective code table. The algorithm is followed:

Step 1: For a given list of symbols, establish a comparable list of probabilities or frequency counts, so that each symbol's related recurrence of occurrence is known.

Step 2: It will sort the lists of symbols accede to frequency, with the most frequently occurs data at the top and the least common at the bottom.

Step 3: Segregate the list into two elements, with the total number of counts, the upper half is act as close to the total of the bottom half as possible.

Step 4: The upper half of the list is committing the binary digit 0, and the lower half is designated the digit 1. This means that the codes for the symbols in the entire first half will start with 0, and the codes in the complete second half will start with 1.

Step 5: Repeat the steps 3 and 4 for each of the two halves, subdividing groups and include the bits to the codes until each symbol has become a corresponding code leaf on the tree [12].

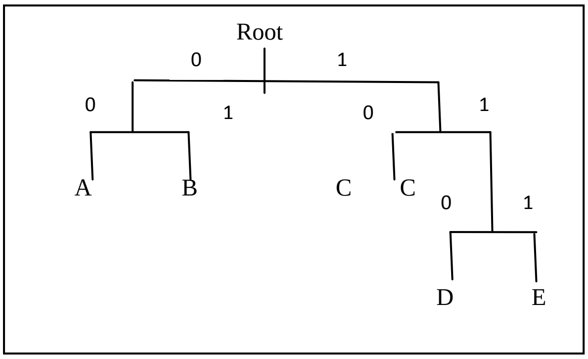

Fig 2: A simple Shannon-Fano tree

4. PROPOSED METHOD

4.1 Theoretical Foundation

The Shannon Fanon Entropy Coding is the easiest way of coding Algorithm for Text or Character. In this paper, propose a new algorithm for LBES Lossless Block-wise Entropy Shannon method for altered with the pixel value contains any number so, it can easily group the pixels and find out the effective compression ratio. Let us consider the following pixel value

Step 1: Original Image

$$Image = \begin{bmatrix} 2 & 4 & 4 & 6 & 7 & 7 & 8 & 8 \\ 2 & 3 & 4 & 5 & 6 & 7 & 8 & 8 \\ 2 & 1 & 2 & 4 & 6 & 7 & 8 & 8 \\ 1 & 1 & 1 & 3 & 5 & 6 & 7 & 7 \\ 1 & 2 & 1 & 2 & 4 & 5 & 6 & 7 \\ 2 & 1 & 2 & 1 & 3 & 4 & 6 & 7 \\ 1 & 1 & 0 & 1 & 2 & 3 & 5 & 7 \\ 1 & 1 & 0 & 1 & 1 & 2 & 5 & 5 \end{bmatrix}$$

Step 2: Count the Probability occurrence of pixels in ascending order.

$\log {}^{1}\!/_{p}$

0011111111111111122222222223334444445555556666667777777777888888

Step 3: Count Probability occurrence of group of pixel for example 1/15 = 1.17

Step 4:Assemble code in DFS according to their frequencies 1 2 7 4 5 6 8 3 0

Step 5: Calculate code table

Symbol	Count	log(1/p)	Code	Subtotal (# of bits)
1	15	1.17	00	30
2	9	0.95	01	18
7	6	0.77	10	12
4	6	0.77	110	12
5	6	0.77	1110	12
6	6	0.77	11110	12
7	6	0.77	111110	12
8	6	0.77	1111110	12
3	3	0.47	11111110	6
0	2	-	111111111	0

Step 6: Entropy Calculation for each block 55.23 for the above block result

Step 7: The total Number of bits is $65 \times 2 = 130$

So, the method can divide the Entropy value with total number of bits

E = 56.13 / 130

E = 0.43

Number of bits needed = 10

Step 8: Repeat this step until the block ends

Entropy calculation

$E = (15 \times 1.17 + 9 \times 0.95 + 6 \times 0.77 + 6 \times 0.77 + 6 \times 0.77 + 6 \times 0.77 + 6 \times 0.77 + 6 \times 0.77 + 3 \times 0.47 + 2 \times 0)$

Therefore, it gets the entropy value of 8×8 matrix pixel image is 56.13. This Entropy value can calculate the total number of bits employed 130, so the methods find each block it contains an entropy value for better compression ratio.

4.2 Algorithm

4.2.1 Compression, Encoding Algorithm

Step 1: Load any image as input.

Step 2: Convert to the required size 8×8 by using Reshape

Step 3: Divide sub block and convert matrix format

Step 4: Arrange ascending order in sub blocks.

Step 5: Assemble code n DFS.

Step 6: Apply LBES Entropy calculation for Each Block.

Step 7: Construct compressed image.

Step 8: Stop.

4.2.2 Decompression, Decoding Algorithm

Step 1: Get a compressed image with a number of quantized ranges.

Step 2: Get the histogram table.

Step 3: Divide into a number of non-overlapping blocks

Step 4: Apply reverse LBES to the histogram table

Step 5: Decode the compressed gray value to original value.

Step 6: Make the conversion matrix to an image.

Step 7: Display the Reconstructed image

Step 8 Compare with quality measurement.

Step 9: Generate CR Table.

Step10: Stop.

4.3 Block Diagram

4.3.1 Encoding

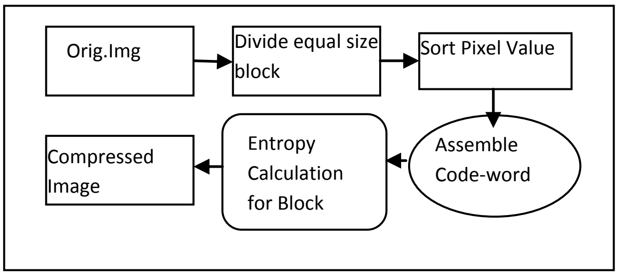

Fig 3: LBES Encoding

4.3.2 Decoding

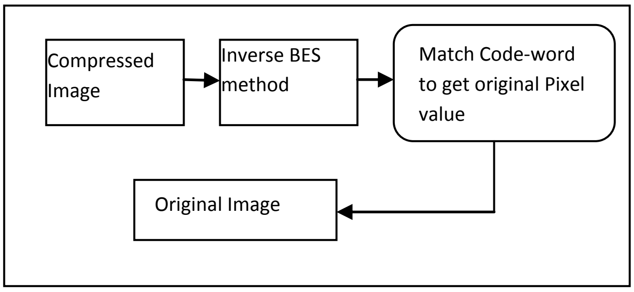

Fig 4: LBES Decoding

5. RESULTS AND DISCUSSION

5.1.1 Experimental Results

The experiments are performed on various standard grayscale image databases to verify the proposed LBES algorithm and it is attained as far as execution time is concerned, the proposed LBES algorithm gives better compression ratio for Lossless compression algorithm. Different size of 256×256 pixels is used as the cover images. The experiments are carried out within the different block size like 16×16, 32×32 to 256×256.

In this paper compression and decompression has been applied on three different grayscale images with different storage size. The compression and decompression process are presented below Fig 5a shows the sample Original and Fig 5b shows reconstructed grayleaf image with LBES Algorithm. In Fig 6a shows the original pirate image and Fig 6b shows reconstructed pirate image. Finally Original cameraman is Fig 7a and Fig 7b shows reconstructed cameraman image.

Fig 5a:Original Image

Fig 5b: Reconstructed Image

Fig 6a:Original Image

Fig 6b: Reconstructed Image

Fig 7a:Original Image

Fig 7b: Reconstructed Image

5.1.2 Quality Measurement Parameters:

An image quality of greater importance is given to sharpness rather than tone reproduction. Subjective image quality measurements are mean square error, PSNR, CR, Bit, Computation Time. When the quality of the images is considered indirectly by means of MSE, it is obvious that AQT has approximately equal degree of MSE. That is to say, the MSEs of the following original Flower image applied with different block size like 16×16 to 256×256. The MSE is the cumulative squared error between the compressed and original image. The equation is defined as

$$MSE = \frac{1}{m\times n}\sum_{m=1}^{M}\sum_{n=1}^{N}[f(m,n)-g(m,n)]^2 \quad (1)$$

The PSNR is defined as

$$PSNR = 10\times\log_{10}\left[\frac{255}{\sqrt{MSE}}\right] \quad (2)$$

The compression ratio is defined as

Compression ration = Original Image / Compressed Image (3)

Entropy value can be calculated from the following equations,

$$Entropy = \sum_{a\in A}\sum_{b\in A}\rho(a,b)\log 2\left(\frac{1}{\rho(a,b)}\right), \quad (4)$$

The image quality parameter is implemented through MATLAB Version 2013a.

5.1.3 Performance Analysis

Lossless compression ratios for Block-wise Entropy Shannon (LBES) are reported in Table 1 (for Quality Measurement for Gray Leaf image). The best compression ratio can be calculated different block size. In this paper, examine 256×256 blocks measured with best entropy value 18.23 than existing image format. This research work is an analysis the novel idea, comparatively Shannon-fanon coding techniques applied only with text or character in the previous research work. But, in this paper presents with image analysis combine with Shannon-fanon technique with block wise comparative analysis. So, this proposed algorithm (LBES) plotted with graph different size of standard test image format.

From Table 1, it is noted with the best compression ratio and Entropy value achieved with LBES method. At the same time noted with the minimum block size starts with minimum compression value with gradually increases the block size increased. In addition, noted with PSNR, MSE and Entropy value for image quality measurement.

Table 1. Quality Measurement for Grayleaf Image

Block-size	MSE	RMSE	PSNR	Comp-Size	Entropy	CR
16 × 16	3395.48	58.27	12.45	228	2.87	3.21
32 × 32	2270.14	47.64	20.34	486	5.65	6.12
64 × 64	1934.56	43.98	28.45	1689	9.45	10.23
128 × 128	1257.20	35.45	34.78	3438	16.43	17.32
256 × 256	670	25.88	40.10	8764	18.23	19.54

In Table 2, Original pirate image data with measurement of PSNR, RMSE, MSE, CR and Entropy value noted with the block size 256×256 PSNR is 39.62.

Table 2. Quality Measurement for Pirate Image

Block-size	MSE	RMSE	PSNR	Comp-Size	Entropy	CR
16 × 16	3350.48	57.88	10.40	192	2.01	2.90
32 × 32	2512.10	50.12	15.25	442	4.65	4.13
64 × 64	2220.14	47.11	25.42	1570	7.46	9.10
128 × 128	1198.40	34.61	30.71	3038	14.41	15.12
256 × 256	788	28.07	39.62	7762	16.23	17.32

From Table 3 shows the measurement of PSNR, RMSE,MSE and Entropy value measured with 16× 16 block size to 256× 256 blocks of the tested image. It is noted that the CR and Entropy values in the block size 256×256 is 15.12 and 14.16. In MSE and RMSE value are gradually decreased it is indicated that the image quality states Lossless quality of image.

Table 3. Quality Measurement for Cameraman Image

Block-size	MSE	RMSE	PSNR	Comp-Size	Entropy	CR
16 × 16	3108.42	55.75	9.39	189	1.78	1.58
32 × 32	2890.21	53.76	15.10	401	3.98	2.10
64 × 64	2664.42	51.61	24.42	1471	6.34	7.30
128 × 128	1325.10	36.40	28.71	2834	12.31	13.10
256 × 256	890	29.83	38.51	6702	14.16	15.12

5.1.4 Comparative Study

In Table 4 compares the compression ratio with existing method with Arithmetic Coding and Shannon- Fanon Coding applied to the standard test image. The LBES method achieves better compression ratio with other existing method for different kinds of grayscale image with different block size. The analysis of existing methods is shown in Table 4.

Table 4. Comparative Study with Existing Methods

Image	Arithmetic Coding	Shannon-Fanon Coding	Proposed LBES
Gray Leaf	16.50	17.50	19.54
Pirate	14.02	15.12	17.32
Cameraman	13.76	14.22	15.12

From Fig.8 shows, the analysis of Peak-Signal-to-Noise-Ratio (PSNR) for standard test images, In Gray Leaf image shows the PSNR value 40.10 for the block size 256×256.

Fig.9 presents Entropy value for calculating the best compression ratio for different block size. The method will be compared three different standard test images. In Pirate image shows the Entropy value for the block size 128×128 is 14.41.

In Fig.10 indicates the compression ratio for different test images with different block sizes, For example Cameraman image shows the compression ratio for the block size 64×64 is 7.30. Fig.11 compare the existing method with LBES method.

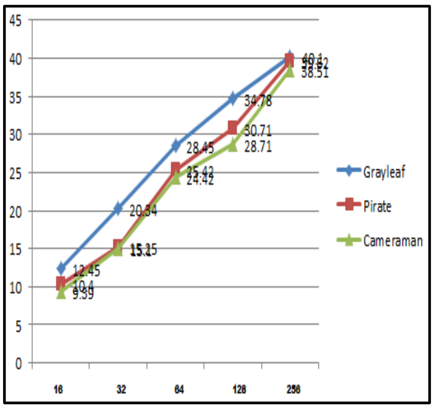

Fig 8:Analysis for PSNR

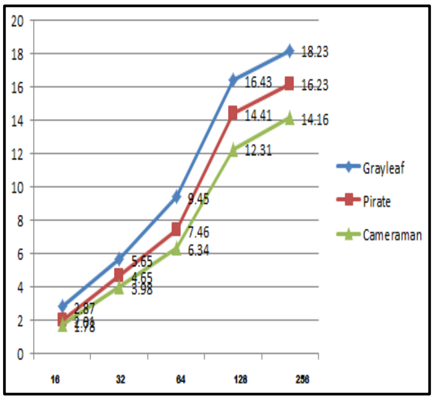

Fig 9:Analysis for Entropy

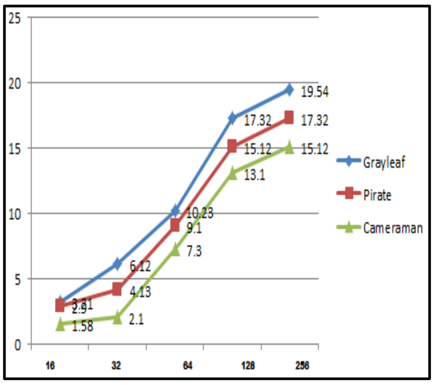

Fig 10:Analysis for CR

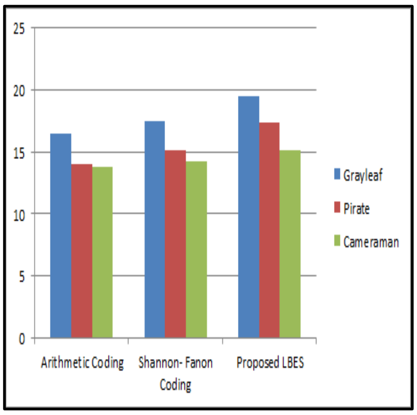

Fig 11:Compare Existing Method

6. CONCLUSION

In this paper, different techniques for compression scheme are studied and compared on the basis of their use in different applications. The LBES method performs block wise compression of the whole image for better compression ratio. The proposed LBES algorithm is most powerful tool to use TIFF, GIFF, JPEG and textual which composes of efficiency and better compression. The LBES method will suitable for grayscale, monochrome images.

7. FUTURE DIRECTION

The further work will be extended to color, multispectral and other video files.

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