New Error Model of Entropy Encoding for Image Compression

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Abstract— Entropy coding provides the lossless compression of data symbols and is a critical component in signal compression algorithm. In our case we have designed a new model which reduces the Interpixel redundancy and have better results as compared to other models like lossless predictive code (LPC) and Differential pulse code modulation (DPCM). Our new proposed Scheme for Huffman coding will achieve higher compression as we have also reduce the standard deviation in the error image tremendously as compare to LPC and DPCM.

Keywords: *Lossless compression, Lossy compression, Redundancy, Lossless predictive model*

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1. INTRODUCTION [1,3]

Image compressionis the application of data compression on digital images. In effect, the objective is to reduce redundancy of the image data in order to be able to store or transmit data in an efficient form. Image compression can be lossy or lossless. Lossless compression is sometimes preferred for artificial images such as technical drawings, icons and comics. This is because lossy compression methods,

Especially when used at low bit rates, introduce compression artifacts. Lossless compression methods may also be preferred for high value content, such as medical imagery or image scans made for archival purposes. Lossy methods are especially suitable for natural images such as photos in applications where minor loss of fidelity is acceptable to achieve a substantial reduction in bit rate.

1.1Redundancy and Irrelevancy[1,9]

Redundancy in general terms, refers to the quality or state of being redundant, that is exceeding what is necessary or normal, or duplication. This can have a negative connotation, especially in rhetoric: superfluous or repetitive, or a positive implication, especially in engineering: serving as a duplicate for preventing failure of an entire system. Data compression is achieved when one of the following redundancies are reduced or removed. An important example of data irrelevancy occurs in the visualization of grayscale images of high dynamic range, e.g. 12 bit or more. It is an experimental fact that for monochrome images 6 to 8 bits of dynamic range is the limit of human visual sensitivity; any extra bit does not add perceptual value and can be eliminated.

1.1.1Types of Redundancies

(A) Coding Redundancy

A great deal of information about the appearance of an image can be obtained from a histogram of its gray level. Let us assume that a discrete random variable r_k in the interval [0, 1] represents the gray levels of an image and that each r_k occurs with the probability $P_r(r_k)$.

$$P_r(r_k) = \frac{n_k}{n} \quad k = 0,1,2..........l-1 \quad (1.1)$$

Where L is the number of gray levels, n_k is the number of times the kth gray levels appear in the image. If the number of bits used to represent each value of r_k is $L(r_k)$ then the average number of bits required to represent each pixel is

$$L_{avg} = \sum L(r_k).P_r(r_k) \quad (1.2)$$

Thus the total number of bits required code an 'M x N' image is (MNL) avg

(B) Inter-pixel Redundancy

The codes used to represent the gray levels of an image have nothing to do with the correlation between pixels. These correlations result from the structural or geometric relationships between the objects of the images.

(C) Psycho- visual redundancy

The brightness of a region, as perceived by the eye, depends on the factors other than simply the light reflected

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by the region. For example, intensity variations can be perceived in an area of constant intensity. Such phenomena results from the fact that the eye does not respond with equal sensitivity to all visual information. Certain information is said to be psycho-visually redundant.

1.2General Image Compression Model [2, 5]

Transform: The main goal of transform stage is to de-correlate the original image data, so that the original signal (image) energy is redistributed among a small set of transform coefficients. The aim of de-correlation is to remove the inter-pixel redundancy; thereby providing a representation that can be coded more efficiently.

The zeroth order entropy of the transformed coefficient is much lower than that of original image. These transforms should be reversible in nature so that the original image can be recovered by the inverse transform; provided no quantization has been performed on forward transform operation.

Quantization / De-quantization Stage: The second stage of quantization / De-quantization is the process that leads to the lossy compression. In the quantization section psycho-visual redundancy in the image is reduced by removing unwanted bits from the transformed coefficient. This stage leads to high compression ratio and distortion in image fidelity.

Entropy Coding / Decoding Stage: The third stage of entropy coding, determines the number of bits required to represent a particular image at a given quantization level. The process of entropy coding and decoding is lossless. It maps the quantized transform coefficients into a bit stream using variable length codes. This stage exploits the coding redundancy.

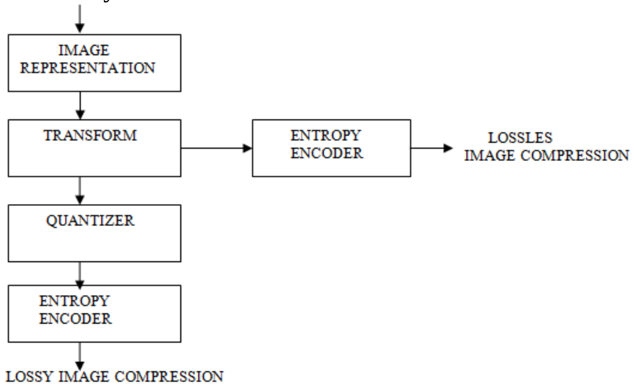

Figure 1

2. MATHEMATICAL BACKGROUND [7, 10]

Now we discuss about different error-free compression approach that does not require decomposition of an image into a collection of bits planes. The approach, commonly referred to a lossless predictive coding, is based on eliminating the inter-pixel redundancies of closely spaced pixels by extracting and coding only the new information in each pixel.

2.1Huffman Coding

A commonly used method for data compression is Huffman coding. One of the most popular techniques for removing coding redundancy is due to Huffman. When coding the symbols of an information source individually, Huffman coding yields the smallest possible number of code symbols per source symbol.

2.1.1Huffman coding algorithm

In a optimum code, symbols that occurs more frequently (have higher probabilities of occurrence) will have shorter code words than symbols that occur less frequently.

The two symbols that occurs least frequently will have the same length.

2.2 Entropy [8]

Entropy encoding which is a way of lossless compression that is done on an image after the quantization stage. It enables to represent an image in a more efficient way with smallest memory for storage or transmission.

The average information per source symbol is known as entropy.

From a source with n symbols, the “Entropy of the source is the minimum theoretical of the average number of bit per symbol”

$$H = -\sum_{i=1}^{n} P_i \log P_i \qquad (2.1)$$

Where P_i is the probability of the i-symbol.

Given a compression scheme, its efficiency can be measured as:

Efficiency = H/(average codeword length).

2.3 Differential entropy [1, 2]

The differential entropy is given by

$$h(x) \leq \frac{1}{2} \log 2\pi e \sigma^2 \qquad (2.2)$$

The differential entropy of a Gaussian random variable is directly proportional to its variance.

The differential entropy for the Gaussian distribution has the added distinction that it is larger than the differential entropy of any other continuously distributed random variable with the same variance. That is, for any random variable X, with variance σ^2

2.3 Global thresholding [9]

The global thresholding is based on the histogram of an image. In this method we do partition of the image histogram using a single global threshold. The success of this technique very strongly depends on how well the histogram can be partitioned.In most applications; there is usually enough variability between images that, even if gobal thresholding is a suitable approach and algorithm capable of estimating automatically the threshold value for each image is required.

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2.4 Various Predictive Coding Models

Now we have discussed about some predictive coding models in following subsections:

2.4.1 Lossless predictive model [9]

When we talk about error-free compression approach then the approach commonly referred to lossless predictive coding, is based on eliminating the inter-pixel redundancies of a closely spaced pixels by extracting and coding only the new information in each pixel.

The new information of a pixel is defined as the difference between the actual and predictive value of that pixel.

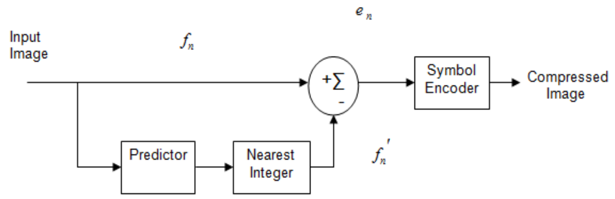

Figure 2.1 Lossless Predictive Encoder

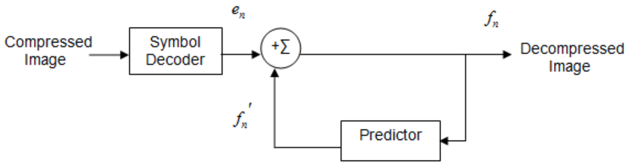

Figure 2.2 Lossless Predictive Decoder

2.5 Differential pulse code modulation [10]

The basic differential encoding system is known as the differential pulse code modulation (DPCM) system. It is most popular as speech encoding system and is widely used in telephone communications.

The DPCM system consists of two major components the predictor and quantizer.

Prediction Error

$e = s - \hat{s}$ (2.3.1)

Reconstruction

$s' = e' + \hat{s}$ (2.3.2)

Reconstruction error = quantization error

$s' - s = e' - e = q$ (2.3.3)

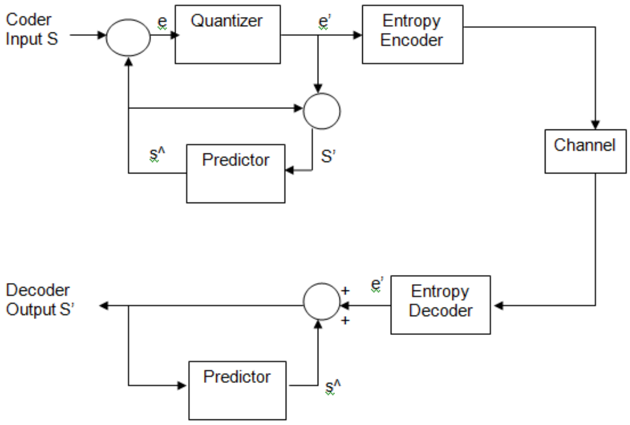

Figure 2.3: Differential Pulse Code Modulation Model

2.6 New Proposed Error Model

Predictive coding is basically used to eliminating the inter-pixel redundancies of closely spaced pixels. The distribution of input data plays a very important role before image transformation stage. If the input data is non uniform in nature then the transformed data will be more uniform type and most of the coefficients will have same value of energy and to encode these coefficients it will require more no of bits as the entropy will be more (As constrained given by Shannon's first fundamental theorem).

Whereas in case opposite to this if anyhow the data is uniform before image transform stage then very few no of the transformed coefficients will have most part of the energy and more transform coefficients will have very less fraction of energy. So in second case most of the coefficients can be eliminated with a reward of very less energy loss and increased compression performance.

Our new model is based on the above fact that. In the proposed model we have tried to generate an error image before image transform stage. The motive behind the generation of this error image is to keep the average pixel value and the standard deviation at minimum so as to make the distribution more uniform to get better compression performance.

The encoder as shown in following figure-2.5 generates the pixel value with the help of past input. First it subtract and add the pixel value with the previous value and then it divides the subtracted and added values with the help of an divider to generate a *Error Image*(e_i).The decoder just perform the reverse operation to retrieve the image.

Encoder

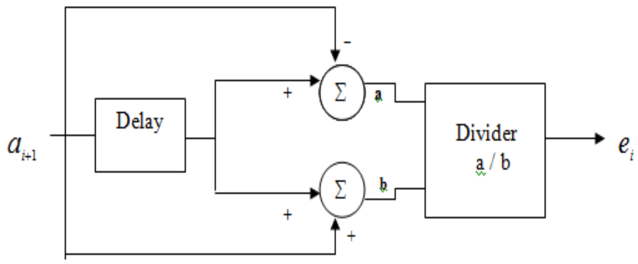

Figure2.4 New Model Encoder

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The encoder value is

$$e_i = \left(\frac{a_{i+1} - a_i}{a_{i+1} + a_i} \right) \quad (2.4.1)$$

Decoder

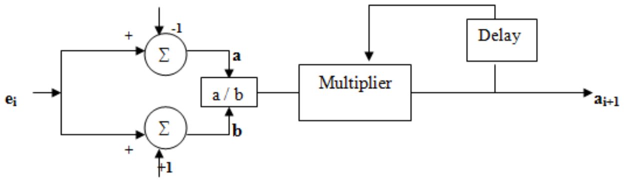

Figure 2.5 New Model Decoder

The decoded value is

$$a_{i+1} = a_i \left(\frac{e_i - 1}{e_i + 1} \right) \quad (2.4.2)$$

4 RESULTS

We will compare our New Proposed model with the LPC.We will prove how our model is better than LPC and Original image.

We have also shown various results and tables depiction output of our work.

4.1 Detailed Analysis

Proposed Model

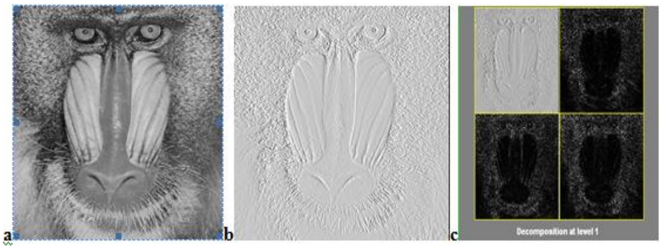

Figure 4.1:a)Original Baboon Image b)Error Image c) Decomposed Image at level 1

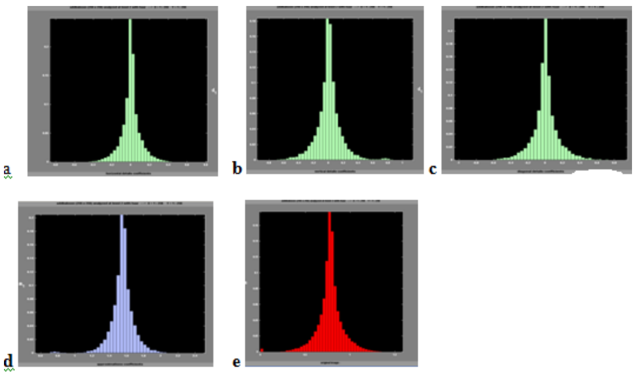

Figure 4.2: a)detail horizontal histogram of baboon b) detail diagonal histogram of baboon c) detail vertical histogram of baboon d) Approximation Histogram e) Original Image Histogram

Table 1 Detailed analyses of baboon error image

New model	Mean	Standard Deviation	max.value	Min.value	entropy
Baboon error image values	0.7756	0.1469	1.573	0	6.367
Approximation values	1.551	0.1436	2.496	0.5509	5.9972
Horizontal values	-6.89e-005	0.1078	0.7994	-0.8509	5.8714
Vertical values	0.00407	0.1726	1.122	-0.947	6.2073
Diagonal values	0.00106	0.1558	0.9309	-1.042	6.1454

LPC Model

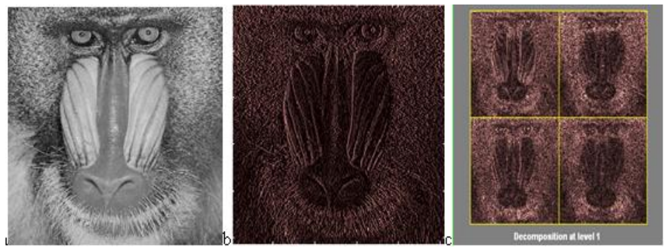

Figure4.3:a)Original Baboon Image b)Error Image c) Decomposed Image at level 1 haar

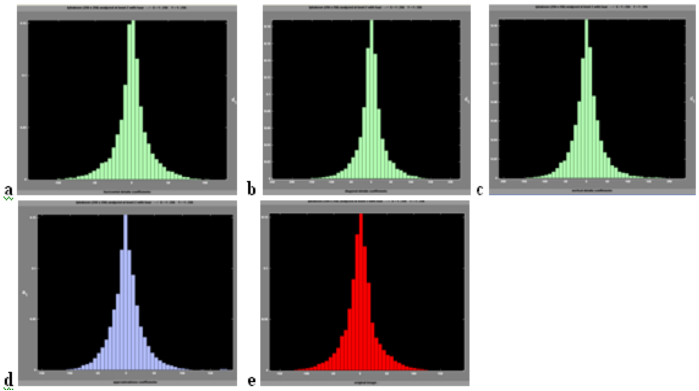

Figure 4.3: a)detail horizontal histogram of baboon b) detail diagonal histogram of baboon c) detail vertical histogram of baboon d) Approximation Histogram e) Original Image Histogram

Table 2: Detailed analyses of baboon LPC image

LPC model	Mean	Standard Deviation	Max.v alue	Min. value	entropy
Baboon error image values	0.4323	32.36	191	-167	6.3285
Approximati on values	0.8646	30.72	187	-155.5	6.3885
Horizontal values	0.00445 6	24.36	127	-139.5	6.405
Vertical values	1.431	37.55	234.5	-208.5	6.2978
Diagonal values	-0.1237	35.23	220	-247.5	6.1051

4.2 Comparison of Retained Energy and Number of Zeros for Different Predictive Model

Proposed Model

Figure 4.4 Analyzation of baboon error Image at Level 2 with Haar

Table 3 Different set of values for baboon error Image

S.no	Global Threshold	Retained Energy (%)	No of Zeros (%)
1	0.2581	98.78	86.13
2	0.5081	97.52	92.72
3	0.8052	96.94	93.62
4	1.012	96.79	93.74
5	1.174	96.78	93.75

LPC Model

Figure 4.5 Analyzation of baboon LPC Image at Level 2 With Haar

Table 3.12 Different set of values for baboon Lpc Image

S.no	Global Threshold	Retained Energy (%)	No of Zeros (%)
1	0.25	100	1.26
2	0.508	100	3.25
3	0.801	100	3.36
4	1.25	100	5.54
5	1.5	100	6.66

5. CONCLUSION

In our proposed model the results give us a new set of pixel values which forms the error image or residual image. The residual distribution is typically zero mean and much more compact than the distribution of original image. By decreasing the mean value, we have also decreased the average codeword length. Then we applied a standard wavelet transform (Haar) at level 2 and calculated the retained energy and the numbers of zeroes and found that the retained energy and number of zeroes for our new model have the better results when threshold value is taken very low. Since the pixel values are uniformly distributed in space domain, then the values will be non-uniformly distributed in frequency domain and all the energy will be contained by only few frequency coefficients and it can be neglected the frequencies having very low values of energy which will helped us to use less bits of data during encoding. So we have concluded that more compact distribution(uniform) results in lower entropy which determines the minimum average code word length that is attainable without information loss, hence achieve a higher compression ratio without information loss.

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