PERFORMANCE ANALYSIS OF INTERPIXEL & PSYCHOVISUAL REDUNDANCY TECHNIQUES FOR IMAGE COMPRESSION

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Abstract: An image is essentially a 2-D signal processed by the human visual system. The signals representing images are usually in analog form. A digital image is basically a 2-Dimensional array of pixels. The advent of digital computer and subsequent development of advanced integrated circuits caused interest to shift from analog to digital compression approaches. To store a typical image contains 1024*1024 pixels with 24 color levels about 3 megabytes are required. With today's computing technique this amount of data is too large for its fast processing and transmission. Therefore, alternative data for representing the same image should be found. Image compression addresses the problem of reducing amount of data needed to represent a digital image.The need for an efficient technique for compression of Images ever increasing because the raw images need large amount disk space seems to be a big disadvantage during transmission and storage.There are many compression techniques already available today. In this paper, we will describe the performance analysis of image compression using interpixel and psychovisual redundancy.

Keywords: Image Compression, lossy compression, lossless compression.

1. Introduction

Now a day, the usage of digital image in various applications is growing rapidly. Video and television transmission is becoming digital and more and more digital image sequences are used in multimedia applications. Sampled and quantized 2-D intensity function used to create a digital image containing a great amount of data. A digital image is composed of pixels, which can be thought of as small dots on the screen and it becomes more complex when the pixels are colored. An enormous amount of data is produced when a two dimensional light intensity function is sampled and quantized to create a digital image. In fact, the amount of data generated may be so great that it results in impractical storage, processing and communications requirements [5].To store a typical image contains 1024*1024 pixels with 24 color levels about 3 megabytes are required. With today's computing technique this amount of data is too large for its fast processing and transmission. Therefore, alternative data for representing the same image should be found.

Image compression addresses the problem of reducing amount of data needed to represent a digital image. This is done by the removal of redundant data contained in the image. This removal of data may be reversible (i.e. the removed data can be fully reconstructed from compressed data) or irreversible (i.e. the removed data can be only partially reconstructed from compressed data). The former kind of compression is called lossless compression, while the latter kind of compression is called lossy compression. The lossless image compression is used in fields where full restoration of original image from compressed one is crucial.

2. Literature Survey

The history of Image Compression dates back more than 35 years. In 1940 the practical application of theoretical work that began, when C.E. Shannon and others first formulated the probabilistic view of information and its representation, transmission and compression. In1966, Bisigani, Richard and when limp, present improved gray level quantization. In 1977, Ziv and Lampel works on LZW coding. In 1987, Neat and Cleary, developed Arithmetic Coding for image compression. In 1991, Rabbani and Jones present tutorial which contains a good discussion of Lossless Predictive Coding. In,2008,Hua Li and Yiming Zhu, publish a research paper in International Colloquium on Computing and Management, titled, Image Compression Based on DPCM-IWT. It dealt with a new lossless image compression method named DPCM-IWPT (Diffential Pulse Code Modulation-Integer Wavelet Packet transform) is proposed, First Wavelet Packet Transform(WPT) and Lifting Scheme (LS) are described.In Feb 2009,Abdul A.Mohamad, Rashid Minhas,Q.M. Jonathan Wu ,Mather A and Sid Ahmed, Dept of Electrical and Computer Engineering, Windsor, Ontario, Canada, publish a research paper, in Canada Research Chair Program, title Fingerprint Image Compression Standard Based on Wave Atoms Decompression and self

C_R is Compression Ratio

For the case of $n_1 = n_2$, $C_R = 1$ and $R_D = 0$, indicating that the first representation of the information contains no redundant data. When $n_2 << n_1$, $C_R \rightarrow \infty$ and $R_D \rightarrow 1$,signifies that highly redundant data. When $n_2 >> n_1$, $C_R \rightarrow 0$ and $R_D \rightarrow -\infty$,indicates that the second data set contains much more data than the original representation, Generally CR=10 (or 10:1) defines that the first data set has10 information carrying units for every 1 unit in the second or compressed data set. Thus corresponding redundancy of 0.9 means 90 percent of the data in the first data set is redundant with respect to the second one.

In order to be useful, a compression algorithm has a corresponding decompression algorithm that reproduces the original file once the compressed file is given. There have been many types of compression algorithms developed. These algorithms fall into two broad types, lossless algorithms and lossy algorithms. A lossless algorithm reproduces the data exactly same as the original one. A lossy algorithm, as its name implies, loses some data. Data loss may be unacceptable in many applications. For example, text compression must be lossless because a very small difference can result in statements with totally different meanings. There are also many situations where loss may be either unnoticeable or acceptable. In image compression, for example, the exact reconstructed value of each sample of the image is not necessary. Depending on the quality required of the reconstructed image, varying amounts of loss of information can be accepted.

4.4 Types of compression

In lossless compression, the reconstructed image after compression is numerically identical to the original image. In lossy compression scheme, the reconstructed image contains degradation relative to the original.

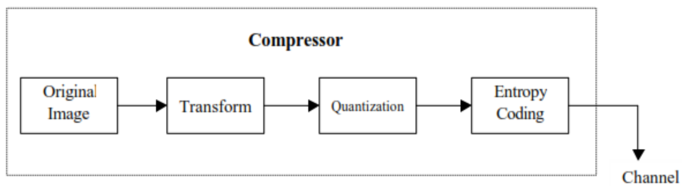
In the case of video, compression causes some information to be lost; some information at a detail level is considered not essential for a reasonable reproduction of the scene. This type of compression is called **lossy compression.** Audio compression on the other hand, is not lossy, it is called **lossless compression**. An important design consideration in an algorithm that causes permanent loss of information is the impact of this loss in the future use of the stored data.

4.5 Image Compression and Reconstruction

Three basic data redundancies can be categorized in the image compression standard.

1. Spatial redundancy due to the correlation between neighbouring pixels
2. Spectral redundancy due to correlation between the color components.
3. Psycho-visual redundancy due to properties of the human visual system.

The spatial and spectral redundancies are present because certain spatial and spectral patterns between the pixels and the color components are common to each other, whereas the psycho-visual redundancy originates from the fact that the human eye is insensitive to certain spatial frequencies. The principle of image compression algorithms are (i) reducing the redundancy in the image data and (or) (ii) producing a reconstructed image from the original image with the introduction of error that is insignificant to the intended applications. The aim here is to obtain acceptable representation of digital image while preserving the essential information contained in that particular data set.



1: Image Compression System

The problem faced by image compression is very easy to define, as demonstrated in figure 1. First the original digital image is usually transformed into another domain, where it is highly de-correlated by using some transform. This de-correlation concentrates the important image information into a more compact form. The compressor then removes the redundancy in the transformed image and stores it into a compressed file or data stream. In the second stage, the quantisation block reduces the accuracy of the transformed output in accordance with some pre-established fidelity criterion. Also this stage reduces the psycho-visual redundancy of the input image. Quantisation operation is a reversible process and thus may be omitted when there is a need of error free or lossless compression. In the final stage of the data compression model the symbol coder creates a fixed or variable-length code to represent the quantiser output and maps the output in accordance with the code. Generally a variable-length code is used to represent the mapped and quantised data set. It assigns the shortest code words to the most frequently occurring output values and thus reduces coding redundancy. The operation in fact is a reversible one. The decompression reverses the compression process to produce the recovered image as shown in figure 2. The recovered image may have lost some information due to the compression, and may have an error or distortion compared to the original image.

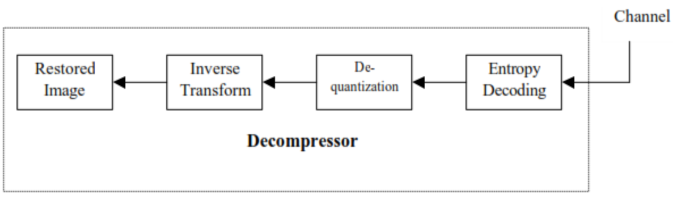


Fig. 2: Image Decompression System

Transforms

This equations shows that transform coefficients are the sum of the effects of the transform on the pixel intensities, overthe whole section of the image to be transformed.The transform is rarely applied to the whole of the image. As the area of the image to which the transform has to be applied increases, the number of calculations also increases proportionally. This suggests that to keep the number of calculations small (and manageable), the area that the transform is applied to should be as small as possible. However, the decorrelation effects on the transform improve, when a larger area of the image is considered, and this in turn improves the compression performance.

In a real system a compromise is established between the compression and the speed of the transform. The effects of decorrelation are not linearly proportional to the area used so it is not possible to theoretically determine the best area to apply the transform to; it has to be done using practical results.

The image is broken into a sub-blocks and the transform is applied to each block separately. Each block then has a set of transform coefficients, which describe it. Although it has been stated that images are highly correlated, this is only true over local areas of the image. There may be little or no correlation between distant sections (100 pixels) of the image. Applying the transform to image blocks exploits the local similarity of the image without losing the benefits of decorrelation in the transform coefficients.

Transforming image blocks also introduces a blocking artifact effect, which can be a major problem. Since the coefficients that describe one block are not related to those describing the surrounding blocks, it is possible for discontinuities to occur along the block edge of compressed images. Blocking artifact is only visible at higher compression rates, in most systems, but can severely reduce the visual quality of a compressor, even if the rate distortion performance is still acceptable. The blocks that the image is broken into do not have to be a fixed size or shape, but they are generally non-overlapping.

Quantization

The transform stage spatially de-correlates the spatial property of the image, but does not always produce compression. Quantization relevant to image coding is discussed in this section and simplified to allow a general rule for the quantization of transform image coefficients to be developed. Quantization is the main stage in case of lossy image compression, where most of the image compression is achieved. Before quantization a transform coefficient may take an infinite range of values, limited only by the accuracy of the medium it is stored in. After quantization the transform coefficient will be represented by a number of discrete values. This could be represented as:

$$Cq = q\,D\,c \qquad (3)$$

where q is the quantisation function, c is the transform coefficients and $cq = \{c0, c1, c2, ...cn\}$.

Linear quantisation is the most basic form of quantisation. The transform coefficients are divided by a quantisation step and the result is converted to an integer, by truncation of the decimal point equation (4).

$$C_q = \text{Integer}\left(\frac{c_i}{q_i}\right) \quad (4)$$

Where q_i is the quantization step

c_i is the transform coefficient

C_q is the integer quantized coefficient.

Various Types of Data Redundancy

In digital image compression, three basic data redundancies can be identified and exploited:

- Inter pixel redundancy
- Psycho-visual redundancy
- Coding redundancy

Data compression is achieved when one or more of these redundancies are reduced or eliminated.

Inter-pixel Redundancy

Another important form of data redundancy is inter-pixel redundancy, which is directly related to the inter-pixel correlations within an image. Because the value of any given pixel can be reasonable predicted from the value of its neighbors, the information carried by individual pixels is relatively small. Much of the visual contribution of a single pixel to an image is redundant; it could have been guessed on the basis of its neighbor's values. A variety of names, including spatial redundancy, geometric redundancy, and inter-frame redundancy have been coined to refer to these inter-pixel dependencies. In order to reduce the inter-pixel redundancies in an image, the 2-D pixel array normally used for human viewing and interpretation must be transformed into a more efficient but usually non-visual format. For example, the differences between adjacent pixels can be used to represent an image. Transformations of this type are referred to as mappings. They are called reversible if the original image elements can be reconstructed from the transformed data set. To reduce the inter-pixel redundancy we use various techniques such as:

- Run length coding.
- Delta compression.
- Constant area coding.
- Predictive coding.
- Psycho-visual Redundancy

Human perception of the information in an image normally does not involve quantitative analysis of every pixel or luminance value in the image. In general, an observer searches for distinguishing features such as edges or textural regions and mentally combines them into recognizable groupings. The brain then correlates these groupings with prior knowledge in order to complet the image interpretation process. Thus eye does not respond with equal sensitivity to all visual information. Certain information simply has less relative importance than other information in normal visual processing. This information is said to be psycho-visually redundant. It can be eliminated without significantly impairing the quality of image perception. Psycho-visual redundancy is fundamentally different from the coding redundancy and inter-pixel redundancy. Unlike coding redundancy and inter- pixel redundancy, psycho-visual redundancy is associated with real or quantifiable visual information. Its elimination is possible only because the information itself is not essential for normal visual processing. Since the elimination of psycho-visual redundant data results in a loss of quantitative information. Thus it is an irreversible process. To reduce psycho-visual redundancy we use quantizer. Since the elimination of psycho- visually redundant data results in a loss of quantitative information. It is commonly referred to as quantization. As it is an irreversible operation (visual information is lost) quantization results in lossy data compression.

5. Performance Analysis

5.1 Procedure for Suppression of inter-pixel redundancy from a digital image:

STEP-1. Read the tricolor digital image in RGB format then convert it into HSV format. Differentiate the three matrices, each denoteing individual color information. Take the first matrix. for example we take 2x4 matrix.

Sig = 0 .6554 0.6006 0.3364 0.5023
0.3720 0.4669 0.3443 0.4164

STEP-2 .Reshape the Sig,

Sig = [0.6554 0.6006 0.3364 0.5023 0.3720 0.4669
0.3443 0.4164]

STEP-3 Quantize each element of Sig by subtracting each one by previous one.

We get d=[0.0548 0.2643 -0.1660 0.1303 -0.0949 0.1226 -0.0721]

STEP -4 Find minimum value in array d, we get absolute minimum value z= .1660 and again we have

d =d+z= [0.2207 0.4302 0 0.2963 0.0711 0.2886 0.0939]

STEP -5 Round d by d/max (d) x (2)-1. We get a1 =[2 3 0 2 0 2 1] and convert it into binary form BIN =[1011001101]

STEP-6 NOW BIN form converts into decimal form

DEC= [2 3 0 3 1 3 1]

STEP-7 Decode= (DEC/max(DEC)) X max(d).we get

Decode=[0.2868 0.4302 0 0.2868 0 0.2868 0.1434]

STEP-8 Decode =decode-z= [0.1209 0.2643 -0.1660 0.1209 -0.1660 0.1209 0.0226]

STEP-9 Reconstruct image matrix using sig array and decode array .then we get receive array

Rec = [0.6554 0.5345 0.3364 0.5023 0.3815 0.5380 0.3461 0.3668]

STEP-10 Reshape receive matrix by help of receive matrix Rec array

0.6554	0.3815
0.5345	0.5380
0.3364	0.3461
0.5023	0.3668

STEP-11 Take the transpose of above matrix to find the receive matrix; Receive matrix=

0.6554	0.5345	0.3364	0.5023
0.3815	0.5380	0.3461	0.3668

STEP-12 To find error we subtract sig matrix from receive matrix.

5.2 Procedure for Suppression of Psycho-visual Redundancy from a digital image:

STEP-1. Read the tricolor digital image in RGB format then convert it into HSV format. Differentiate the three matrices, each denoteing individual color information. Take the first matrix. for example we take 2x4 matrix.

Sig = 0.9221 0.9158 0.9111 0.9137
0.9242 0.9110 0.9058 0.9111

STEP- 2 Find the maximum value in above matrix.

Max=.9242

STEP-3 Rreshape sig matrix-{ sig/max(sig) } $2^{k}-1$ We get matrix A

A = 2.9930 2.9725 2.9574 2.9657
3.0000 2.9570 2.9401 2.957

STEP-4 Round matrix A and reshape matrix A

A= 3 3 3 3
3 3 3 3

A= [3 3 3 3 3 3 3 3]

STEP-5. Convert each element of A in to binary form. each element having length of N.

We get coded =[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]

STEP -4.Decode above coded array to get decode matrix.

Decode =[3 3 3 3 3 3 3 3]

STEP-5 Decode array change into receive matrix by using following formula.

Receive matrix= (decode/($2^{k}-1$)) X max

0.9242	0.9242
0.9242	0.9242
0.9242	0.9242
0.9242	0.9242

STEP-11 Take the transpose of above matrix to find the receive matrix

Receive matrix=0.9242 0.9242 0.9242 0.9242
0.9242 0.9242 0.9242 0.9242

STEP-12 To find error we subtract Sig matrix from Receive m

In this simulation project, we take a colored image for compression .We used method for compression purpose is lossy compression inter-pixel and psycho-visual redundancy .For image compression we first transform color image into three individual frame (red frame, green frame, blue frame) then this individual frame transforms into ntsc or hsv model .This model shows as image matrix (N x M), this image matrix show pixels value. For image compression by psycho-visual and inter-pixel redundancy algorithm, we are using quantization and DPCM. Image compression is done by varying bits per pixel. After compression of each frame decompression is done. After the decompression we combine each individual frame and transformed it into ntsc or hsv model. This ntsc or hsv model then transformed into decompressed colour image .Here we are taking image size of 200 x 300.

Table 1. Comparative results ofInterpixel and Psychovisual redundany

	No.of bits in compressed image(n1)	CR	Rd	Error=f'(x,y)-f(x,y)	SNR dB	MSE
Psycho-visual redundancy	200x300x1	8	0.875	28.9725	2.7429	0.013990096
	200x300x2	4	0.75	10.194	8.356	0.001731961
	200x300x3	2.66	0.625	2.7911	14.6912	0.000129837
	200x300x4	2	0.5	0.8829	20.5967	1.29919E-05
	200x300x5	1.66	0.375	0.3727	24.3485	2.31509E-06
	200x300x6	1.33	0.248	0.1846	27.2765	5.67953E-07
	200x300x7	1.14	0.122	0.1038	30.2325	1.79574E-07
	200x300x8	1	0	0.0551	33.1248	5.06002E-08
Inter-pixel redundancy	200x300x1	8	0.875	8.9415	6.1525	0.001332507
	200x300x2	4	0.75	3.9871	8.1473	0.000264949
	200x300x3	2.66	0.625	1.1713	13.3999	2.28657E-05
	200x300x4	2	0.5	0.3348	19.1094	1.86818E-06
	200x300x5	1.66	0.375	0.1661	22.2282	4.5982E-07
	200x300x6	1.33	0.248	0.0747	25.6947	9.30015E-08
	200x300x7	1.14	0.122	0.0366	28.6402	2.2326E-08
	200x300x8	1	0	0.0184	31.6863	5.64267E-09

Variation of SNR dB Vs CR are shown in Fig . 3

Variation of MSE Vs Compression Ratio are shown in Fig 4, Red line shown for psycho-visual redundancy algorithm and Blue line for inter-pixel redundancy algorihm

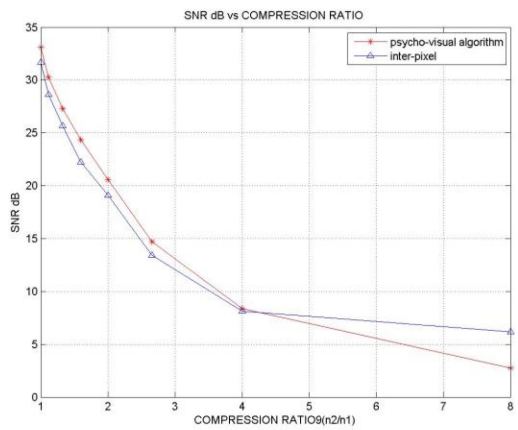


Fig.3 SNRdB Vs Compression Ratio (n2/n1)

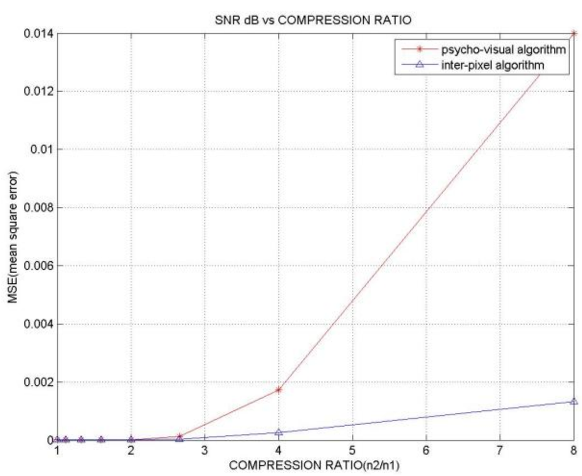
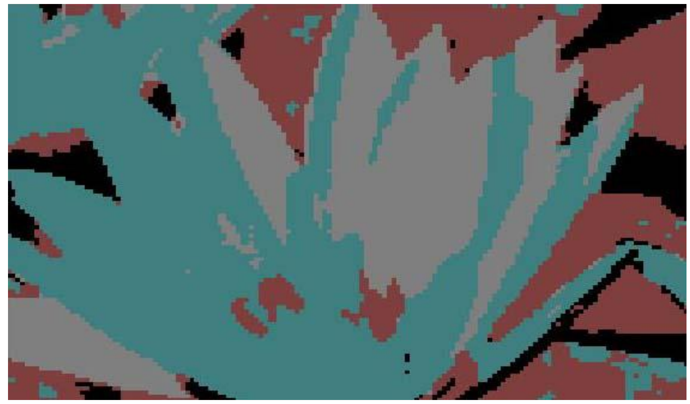


Fig.4:MSE vs. Compression Ratio (n2/n1)

Fig.5 Original Image of Water -Lilies



Bit/pixel=1, CR=8 ,SNR=2.7429 dB

Fig: 6: Compressed Image using psycho-visual redundancy algorithm

Bit/pixel=2, CR=4 ,SNR=8.356 dB

Fig: 7 Compressed Image using psycho-visual redundancy algorithm

Bit/pixel=1, CR=8, SNR= 6.1525 dB

Fig: 8 Compressed Image using inter-pixel redundancy

algorithm

Bit/pixel=2, CR=4, SNR=8.1473 dB

Fig: 9 Compressed Image using inter-pixel redundancy algorithm

6. Conclusion

In this paper, we have analyse the performance of interpixel and pycsho-visual redundancy technique for image compression and also we summarized the what is data compression, characteristics of image compression, need of compression, principles behind compression, different classes of compression techniques with the help of literature survey and got the satisfactory result.

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