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RESEARCH PAPER

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IMAGE DENOISING USING LU DECOMPOSITION AND FEATURE EXTRACTION USING GLCM

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***Abstract*:** This paper proposes the removal of noise using LU decomposition and feature extraction using Gray level co-occurrence matrix (GLCM). The size of the image is reduced after decomposition and the compression ratio is calculated. When the compression ratio is less, the noise present in the data is also less. The image data contains contains redundant information and therefore it is necessary to decompose the data. There are many image decomposition techniques and they are spatial domain and frequency domain. Spatial domain operates the image on gray scale values. Texture is an important feature of an image. GLCM is used to obtain the second order statistical features for an image and it operates on spatial domain. The features of an image include color, texture, shape or domain specific features. . The texture features such as energy, entropy, homogeneity, correlation and contrast have been calculated. The aim of the paper is to extract the texture features of an image and to compare the size of an image before and after decomposition. The compression ratio is calculated and the performance of an image is evaluated before and after LU decomposition.

Keywords: LU decomposition ,texture extraction, compression ratio, GLCM

1. INTRODUCTION

An image contains redundant information and it needs more space for storage. Thus image compression plays a vital role in medical imaging [1]. Compression of data is very essential in data storage and it is of two types namely lossless and lossy decomposition. In lossless data compression, the original data can be recovered from the compressed data without any loss [7]. Lossy compression techniques involve some loss of information and the compressed image has more noise added to the data [5]. LU decomposition is used for decomposition of the data and it removes the noise present in an image[4]. In images, the neighboring pixel is correlated and spatial values are obtained by the redundancy between the neighboring pixel values. The size of the image before and after decomposition has been calculated and also the compression ratio is calculated for the images[9].

Texture is an important feature that identifies the object in an image. The texture is characterized by the spatial distribution of pixels in the neighborhood of an image[2]. The spatial dependence of gray levels is represented by a two dimensional matrix known as GLCM and it is used for texture analysis[3]. The GLCM matrix specifies the texture of an image that, how often the pairs of pixels with specific values occur in an image[8]. The statistical measure is then extracted from the GLCM matrix. The image is represented as a two dimensional array as a function of two variables. The textural features represent the spatial distribution of gray tonal variations within a specified area[6].

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2. IMAGE DENOISING

A $m \times n$ matrix is said to have LU decomposition if there exists matrices L and U with the following properties:

(i) L is $m \times n$ lower triangular matrix with all diagonal entries being 1.
(ii) U is $m \times n$ matrix in some echelon form.
(iii) $A = LU$.

Steps:

[A] is factored or “decomposed” into lower [L] and upper [U] triangular matrices.

Substitution step: [L] and [U] are used to determine a solution {X} for a right hand side {B} which can be solved by back substitution for {X}.

The matrix m x n for the equation AX=b can be solved by forward or backward substitution.

3. GRAY LEVEL CO-OCCURENCE MATRIX (GLCM)

In statistical texture analysis, the texture features are obtained from the statistical distribution of intensities at specified position relative to each other in an image. The texture statistics are classified into first order, second order and higher order statistics. The Gray level co-occurance matrix (GLCM) is a method of extracting second order statistical texture features. First order texture measures are statistics calculated from original image and do not consider pixel neighbour relationships. GLCM considers the relation between two pixels at a time, called reference pixel and a neighbour pixel[7].

GLCM is a matrix where the number of rows and columns are equal to the number of gray levels G in an image. The matrix element $P(i, j \mid \Delta x, \Delta y)$ is the relative frequency with two pixels with intensity i and j separated by a pixel distance Δx, Δy. The matrix element $P(i, j \mid d, \theta)$ contains the second order statistical probability values for changes between gray levels i and j at a particular displacement distance d and particular angle θ. Element [i, j] of the matrix is generated by counting the number of times a pixel with value i is adjacent to a pixel with value j. Each entry is the probability that a pixel with value i will be found adjacent to a pixel of value j.

A gray tone spatial dependency matrix is computed for a given image and a set of textural features are extracted from this matrix. These features contain information about image textural characteristics such as homogeneity, energy, entropy, correlation, contrast of the image. The texture features are derived using four angles such as 0°, 45°, 90°, 135°. The texture information of an image is contained in GLCM matrix. Haralick textural features were computed from this matrix and these measures represent the textural characteristics of an image. These measures corresponds to specific textural characteristics of an image such as homogeneity, contrast and some indicates the complexity and nature of gray tone transition present in an image.

Consider a 4*4 image represented with four gray-tone values 0 through 3. The test image and the general form of GLCM image is shown in the below table 1 and table 2.

Table 1: Test Image

0	0	1	1
0	0	1	1
0	2	2	2
2	2	3	3

Table 2: General form of GLCM

Gray Tone	0	1	2	3
0	(0,0)	(0,1)	(0,2)	(0,3)
1	(1,0)	(1,1)	(1,2)	(1,3)
2	(2,0)	(2,1)	(2,2)	(2,3)
3	(3,0)	(3,1)	(3,2)	(3,3)

The values of the matrix of four orientation angles 0, 45, 90 and 135 degrees were given below.

θ = 0°

4	2	1	0
2	4	0	0
	0	6	1
	0	1	2

θ = 45°

4	1	0	0
1	2	2	0
0	2	4	1
0	0	1	0

θ = 90°

6	0	2	0
0	4	2	0
2	2	2	2
0	0	2	0

θ = 135°

2	1	3	0
1	2	1	0
3	1	0	2
0	0	2	0

4. EXPERIMENTAL ANALYSIS

In this paper, the textural features are calculated in the spatial domain and the statistical nature of texture is taken into consideration. It is based on the assumption that the textural information of an image I is contained in the overall or average spatial relationship which the gray tones in the image have to one another. The textural features such as energy, entropy, correlation, contrast and homogeneity of the sample images were calculated using GLCM matrix. The textural features of sample images was given in the below table 3.

Table 3: Textural features of an image

IMAGE	SIZE	GRAY SCALE IMAGE (KB)	SIZE OF THE	(LU) KB	RATIO (%)
FLOWER.JPG	31.7	28.2	5.12	4.76	14.13
PILLAR.JPG	46.3	43.9	4.84	5.48	5.96
GARDEN.JPG	92.8	88.4	7.18	5.48	3.64
DEER.JPG	58.7	55.1	6.37	5.39	9.39
SCENE.JPG	118	106	5.63	5.26	4.88

In the next step, LU decomposition was applied to an image. This decomposition method decomposes the image into two parts L and U, which represents the lower and upper elements of the given image respectively. The original image can be obtained by multiplying L*U, where the minor difference can be obtained due to round-off values. Data compression normally provides a compression ratio of 2 to 10 to both binary and gray scale images. The experimental result reveals that LU decomposition is applied for different images with jpg file format. The compression ratio is computed for various images. Using LU decomposition technique, the compression ratio achieved is less than 20. The reduced compression ratio specifies the noise present in the data is also reduced. The size of the iginal, decomposed image and also the compression ratio is shown in the below table 4.

	TEXTURAL FEATURES AND FOUR ORIENTATION ANGLES			
	Contrast			
IMAGE	0	45	90	135
DEER	0.151	1.524	2.0128	2.3211
FLOWER	0.041	0.5309	0.8333	1.0055
SCENE	0.339	1.7527	2.2115	2.6139
GARDEN	0.855	4.2992	5.0338	5.2924
PILLAR	0.292	1.1277	1.4135	1.5278

	TEXTURAL FEATURES AND FOUR ORIENTATION ANGLES			
	Correlation			
IMAGE	0	45	90	135
DEER	0.975	0.7563	0.6784	0.629
FLOWER	0.973	0.6531	0.4553	0.344
SCENE	0.945	0.7211	0.6479	0.5832
GARDEN	0.874	0.3712	0.2641	0.2269
PILLAR	0.959	0.8439	0.8038	0.7874
	TEXTURAL FEATURES AND FOUR ORIENTATION ANGLES			
	Energy			
IMAGE	0	45	90	135
DEER	0.117	0.0492	0.0433	0.0406

FLOWER	0.292	0.1517	0.122	0.1122
SCENE	0.135	0.0861	0.0768	0.0699
GARDEN	0.074	0.0339	0.031	0.0305
PILLAR	0.148	0.122	0.114	0.1106
	TEXTURAL FEATURES AND FOUR ORIENTATION ANGLES			
	Entropy			
IMAGE	0	45	90	135
DEER	2.405	3.3369	3.4497	3.4996
FLOWER	1.477	2.2476	2.4217	2.4835
SCENE	2.459	3.0007	3.0943	3.1611
GARDEN	3.042	3.6752	3.7233	3.7403
PILLAR	2.356	2.7211	2.8084	2.8437

Table 4: Textural features and four orientation angles.

	TEXTURAL FEATURES AND FOUR ORIENTATION ANGLES			
	Homogeneity			
IMAGE	0	45	90	135
DEER	0.9252	0.6784	0.64	0.6229
FLOWER	0.9794	0.8064	0.73	0.6985
SCENE	0.8784	0.7372	0.70	0.6706
GARDEN	0.7736	0.5511	0.51	0.5074
PILLAR	0.9083	0.8269	0.85	0.7932

5. CONCLUSION

The above result shows that LU decomposition is a better compression method to reduce the noise in an image. There are many techniques for image data compressions like Variable length coding, Huffman coding, Predictive coding. The data compression techniques provide a compression ratio of 2 to 20 for both binary and gray scale images. In this paper LU decomposition is applied for different images with JPG file format. The features such as energy, entropy, correlation, contrast and correlation of an image were extracted using GLCM matrix. The texture feature of an image shows the relationship between the pixels in the neighborhood.

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