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Wavelet based Shape Descriptors using Morphology for Texture Classification

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Wavelet based Shape Descriptors using Morphology for Texture Classification

P. Kiran Kumar Reddy [α] , Vakulabharanam Vijaya kumar [σ] & B. Eswara Reddy [ρ]

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I. Introduction

The term texture is somewhat misleading term in computer vision and there is no common or unique definition for texture. Many researchers defined textures based on their specific application. Initially the word texture is taken from textiles. In textures the term texture refers to the weave of various threads tight or loose, even or mixed [2]. The texture provides structural information based on region discrimination shape, surface orientation and spatial arrangement of the object considered [3, 4, 5, 6]. Classification refers; the way different textures or images differ with textural properties or primitives. These textural properties can be statistical, structural and combination of both. One of the oldest, popular and still considered as the bench mark method for classification of textures is the Gray Level Co-occurrence Matrix (GLCM) [7].

The GLCM computes the relative grey level frequencies among the adjacent pair of pixels. Today mostly the GLCM is combined with other methods and it is rarely used individually [8, 9, 10]. Signal processing methods based on wavelets [11, 12, 13] and curvelet transforms [14, 15] are also widely used for texture classification. The present paper derived a classification method on the wavelet transforms using morphological gradient on the shape descriptors derived on the cross diagonal texture unit. The rest of the paper is organized as below. The section two and three describes the basic concepts of wavelets and morphology. The section four describes the proposed method. The section five and six describes the results and discussions followed by conclusions.

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II. Basic Concepts of Wavelets

Today the methods based on the Discrete wavelet transform (DWT) are efficiently and successfully used in many scientific fields such as pattern recognition, signal processing, image segmentation, image compression, computer vision, video processing, texture classification and recognition [16, 17]. Many research scholars showed significant interest in DWT transform based methods due to its ability to display image at different resolutions and to achieve higher compression ratio.

An image signal can be analyzed by passing it through an analysis filter bank followed by a decimation operation in the wavelet transforms [18, 19]. At each decomposition stage the analysis filter bank consists of a low pass and a high pass filter. When the signal goes through these filters it divides into two bands. The averaging operation is known as the low pass filter, extracts the coarse information of a signal. The detail information of the signal is achieved by the high pass filter, which corresponds to a differencing operation. The output of the filtering operations is then decimated by two [20, 21].

By performing two separate one-dimensional transforms one can accomplish a two-dimensional transform. For this Firstly, the image is filtered along the x-dimension using low pass and high pass analysis filters and decimated by two. On the left part of the matrix Low pass filtered coefficients are stored and on the right part of the matrix the high pass filtered coefficients are stored. Because of decimation the total size of the transformed image is same as the original image, which is shown in Fig. 1. Then, it is followed by filtering the sub image along the y-dimension and decimated by two. Finally, the image splits into four bands denoted by low-low (LL), high-low (HL), low-high (LH) and high-high (HH) after one-level decomposition as depicted in Fig. 2. Fig. 3 shows second level of

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filtering. This process of filtering the image is called 'Pyramidal decomposition' of image.

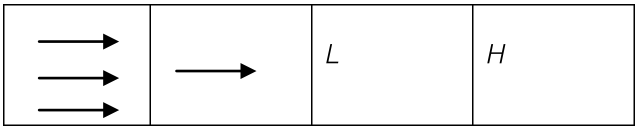

Figure 1 : Horizontal Wavelet Transform.

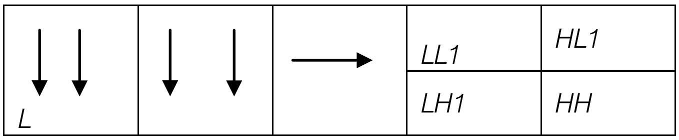

Figure 2 : Vertical wavelet transform for Fig.1.

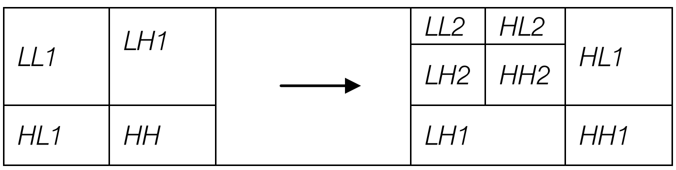

Figure 3 : Second level wavelet transforms.

III. Basic Concepts of Morphology

One of the well defined non-linear theories of image processing is mathematical morphology [19, 22]. Mathematical morphology defines shape and form of the object and it is basically known for its geometry oriented nature. That's why mathematical morphology provides a basic frame work for effective analysis of the object shape features such as size, connectivity and orientation. These features are not easily derived by linear approaches. Mathematical morphology can be applied to binary or gray level images. The morphological operations plays a vital role in boundary and edge detection, noise removal, image enhancement, pre-processing, segmentation, in medical image processing for finding abnormalities and size and volume of the tissues etc. The main advantage of mathematical morphology is all its *operations are defined over two simple operations i.e. dilation and erosion.*

The fundamental or basic step in morphology is to compare the given objects to be analyzed, classified, pre-processed etc. with an object of known shape termed as a Structuring Element (SE). The image transformation will be resulted in morphology by comparing the object under study (analogous to universe) with a defined shape or SE. The shape of the defined SE element plays a crucial role in morphological processing.

Two basic morphological operations – erosion and dilation are based on Minkowski operations as given in equation (1) and (2)

$$X \ominus B = \bigcap_{y \in B} X_y \qquad (1)$$

$$X \oplus B = \bigcup_{y \in B} X_y \qquad (2)$$

Where:

$$X_y = \{ x + y : x \in X \} \qquad (3)$$

$$\hat{B} = \{ b : -b \in B \} \qquad (4)$$

B and $\hat{B}$ are Structuring elements

Dilation in general makes objects to grow or dilate in size. Erosion makes objects to shrink. The amount and the way that they expand or shrink depend upon the selection of the structuring element. Dilating or eroding without the knowledge of structural element makes no more sense than trying to low pass filter an image without specifying the filter.

Dilation grows or dilates or closes the gaps. Erosion in general shrinks or widens the gaps. The amount and the way they expand or shrink and closes and widens gaps depends upon the selected SE. Dilating or eroding without the knowledge of SE makes no sense than trying to low-pass filter an image without specifying the filter.

Another important pair of morphological operations are closing and opening. They are defined in terms of dilation and erosion, by equations (5) and (6) respectively

$$X \bullet B = (X \oplus B) \Theta B \qquad (5)$$

$$X \circ B = (X \Theta B) \oplus B \qquad (6)$$

Dilation followed by erosion is known as closing. Closing connects the objects that are close to each other, fills up small gaps and smoothes the outline of the object by filling up narrow holes. Opening is nothing but erosion followed by dilation. Opening widens small holes and smoothes the objects. Opening operation decreases the size of bright, small details with no prominent effect on the darker gray levels.

Morphological gradient is derived in the present study by evaluating the difference between Dilation and erosion over a 3 x 3 neighborhood.

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IV. Proposed Wavelet based Morphological Gradient Binary Cross Diagonal Shape Descriptors Texture Matrix (WMG-BCDSDTM) Classification Methodology

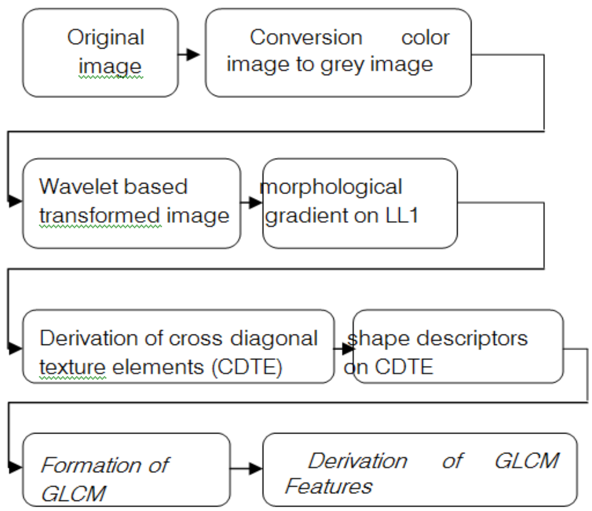

Figure 4 : Block diagram for proposed MGSD Method

The present paper converted the color is images using RGB quantization process by using 7-bit binary code of 128 colors.

a) Derivation of Wavelet based Morphological Gradient Binary Cross Diagonal Shape Descriptors Texture Matrix (WMG-BCDSDTM)

The Texture Unit (TU) and Texture Spectrum (TS) approach was introduced by Wang and He [20]. The TU approach played a significant role in texture analysis, segmentation and classification. The frequency of occurrences of TU in an image is called Texture Spectrum (TS). Several textural features are derived using TS for wide range of applications [4].

In the literature most of the texture analysis methods using texture units based on 3x3 neighboring pixels obtained the texture information by forming a relationship between the center pixel and neighboring pixels. One disadvantage of this approach is they lead to a huge number of texture units 0 to 38-1 if ternary values are considered otherwise 0 to 28-1 texture units if binary values are considered. To overcome this Cross Diagonal Texture Unit (CDTU) is proposed in the literature [1]. Based on the CDTU values Cross diagonal texture matrix (CDTM) is computed [1]. On the CDTM the GLCM features are evaluated for efficient classification [1]. In the CDTM approach the 8 neighboring pixels of a 3x3 window are divided into two sets called diagonal and cross Texture Unit Elements (TUE). Each TUE set contains four pixels. The typical dimension of CDTM is 80 x 80. To reduce this dimension CDTU is evaluated using binary representation instead of ternary. In this the Binary CDTM (BCDTM) contains a dimension of 16 x 16. The elements CDTM and BCDTM can be ordered into 16 different ways [1]. To overcome this, shape descriptors are derived on BCDTM in the present paper in the following way.

In the present paper initially wavelet based morphological gradient image is obtained. On this binary texture unit elements (TUE) are obtained. Then the TUE's are divided into Binary Diagonal Texture Unit Elements (BDTUE) and Cross Diagonal Texture Unit Elements (BCTUE) as shown in Fig.5. Then four elements of the BDTUE and BCTUE are organized as a 2x2 grid as shown in Fig.5. Then on the 2x2 grid shape descriptors (SD) are evaluated. From this WMG-BCDSDTM is derived as shown in Fig.5.

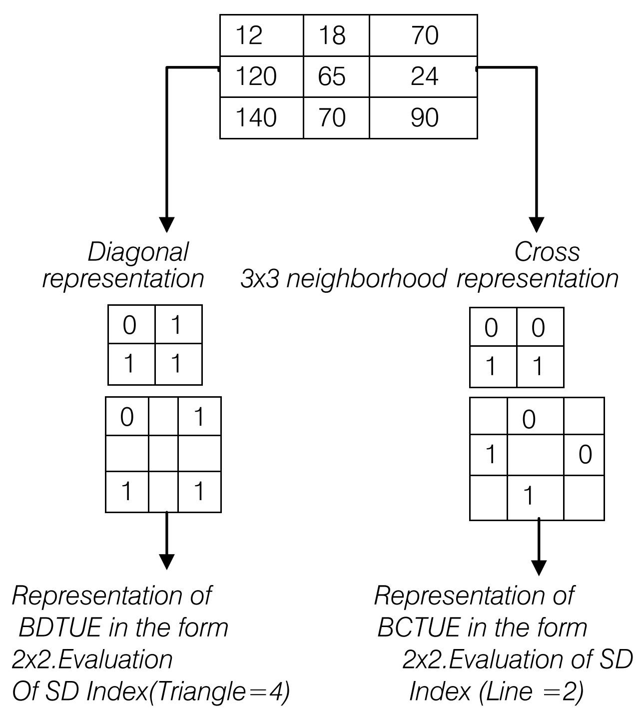

Figure 5 : Formation of WMG-BCDSDTM

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The advantage of shape descriptors is they don't depend on relative order of texture unit weights. The TU weights can be given in any of the four forms as shown in Fig.6. The relative TU will change, but shape remains the same.

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

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

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

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

Figure 6 : Four different ways of assigning weights to TU on a 2x2 grid

b) Derivation of Shape Descriptors (SD) on a 2x2 grid

This section presents shape descriptors and also the indexes that are given to shape descriptors. In the proposed Shape Descriptors (SD) the TU weights can be taken in any order. It results the same shape.

Hole shape (Index 0): The all zero's on a 2x2 grid represents a hole shape as shown in the Fig.7. It gives a TU as zero.

0	0
0	0

Figure7 : Hole shape on 2x2 grid with index value 0

Dot shape (Index 1): The TU with 1, 2, 4 and 8 represents a dot shape. The dot shape will have only a single one as shown in Fig.8.

1	0
0	0

0	1
0	0

0	0
0	1

0	0
1	0

Figure 8 : The four dot shapes on a 2x2 grid with index value 1

Horizontal or Vertical line shape (Index 2): The TU 3, 6, 9 and 12 represents a horizontal or vertical line. They contain two adjacent ones as shown in Fig.9.

1	1
0	0

0	1
0	1

0	0
1	1

1	0
1	0

Figure 9 : Representation of horizontal and vertical lines on a 2x2 grid with index 2

Diagonal Line shape (Index 3): The other two adjacent one's with TU values 5 and 10 represents diagonal lines as shown in Fig.10.

0	1
1	0

1	0
0	1

Figure 10 : Representation of diagonal line on a 2x2 grid with index 3

Triangle shape (Index 4) : The three adjacent one's with TU values 7, 11, 13 and 14 represents triangle shape as shown in Fig.11.

	0	1	2	3	4	5
0						
1						
2						
3						
4			X			
5						

1	1
0	1

0	1
1	1

1	0
1	1

1	1
1	0

Figure 11 : Representation of triangle shape on a 2x2 grid with index 4

Blob shape (Index 5) : All one's in a 2x2 grid represents a blob shape with TU 15. This is shown in Fig.12.

1	1
1	1

Figure 12 : Representation of blob shape on a 2x2 grid with index 5

The detailed formation process of Wavelet based Morphological Gradient Binary Cross Diagonal Shape Descriptor Texture Matrix (WMG-BCDSDTM) is shown in Fig.5. There are only six shape descriptors (0 to 5) on a 2x2 image. Therefore the WMG-BCDSDTM dimension is reduced to 6x6. On this WMG-BCDSDTM the GLCM feature parameters like contrast, correlation, energy and homogeneity are evaluated as given in equation 11, 12, 13 and 14.

$$Energy = \sum_{i,j=0}^{N-1} -ln(P_{ij})^2 \tag{11}$$

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij}\ (i-j)^2 \tag{12}$$

$$Homogenity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \tag{13}$$

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{14}$$

Where P_{ij} is the pixel value of the image at position (i, j), μ is mean and σ is standard deviation.

V. Results and Discussions

To test the efficiency of the proposed method the present paper evaluated above GLCM features for 0°, 45°, 90° and 135° with distance of one for Car, Water Water and Elephant images collected from Google database with a resolution of 256x256. The images are as shown in Fig.13.

The Table 1, 2 and 3 indicates the average value of above GLCM features for 0o, 45°, 90° and 135° 135o with distance of one on the WMG-BCDSDTM for

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the water, car and Elephant textures respectively. Based on the values of GLCM features a classification algorithm1 is derived as shown below.

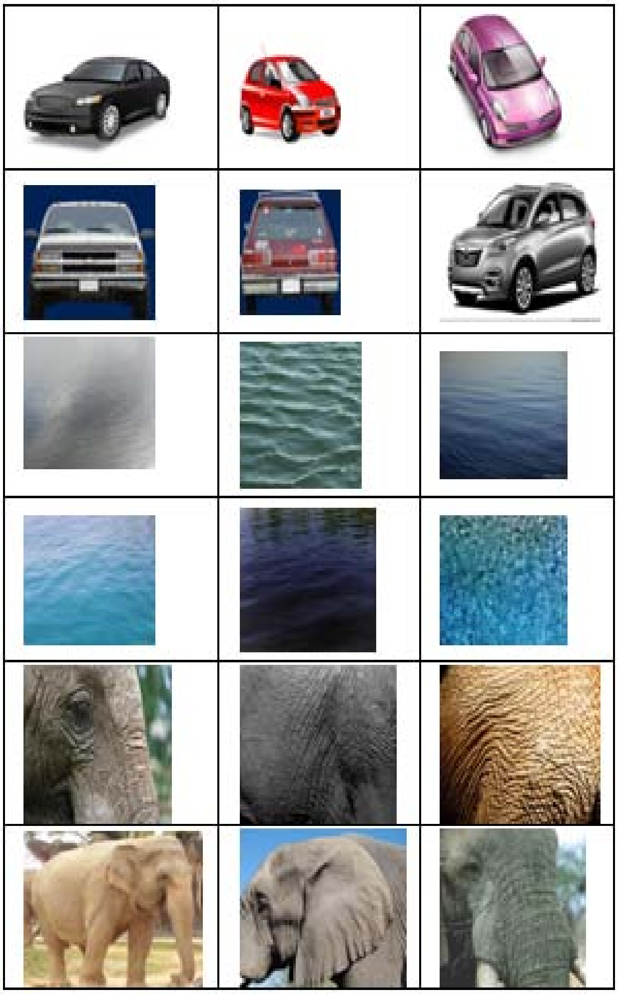

Figure 13 : Car, Water and Elephant textures.

Table 1: GLCM features on WMG-BCDSDTM of Water Texture.

	Average contrast	Average correlation	Average energy	Average homogeniety
W_1	34821.5	-0.046	0.165	0.339
W_2	17511.5	-0.044	0.165	0.302
W_3	14834.4	0.086	0.164	0.399
W_4	27787.7	-0.056	0.167	0.304
W_5	19838.6	-0.033	0.165	0.303
W_6	40908.3	-0.046	0.165	0.329
W_7	46419.8	-0.059	0.164	0.313
W_8	23657.8	-0.059	0.166	0.302
W_9	35427.6	-0.043	0.164	0.32
W_10	24426	-0.0261	0.165	0.311

Table 2 : GLCM features on WMG-BCDSDTM of Car Textures.

	Average contrast	Average correlation	Average energy	Average homogeniety
El_1	16821	-0.046	0.166	0.2
El_2	15175.5	-0.080	0.167	0.201
El_3	16000.4	0.043	0.164	0.297
El_4	13833.9	0.056	0.164	0.298
El_5	13042.6	0.019	0.165	0.298
El_6	18526.6	0.026	0.164	0.26
El_7	11079.5	-0.081	0.166	0.209
El_8	13708.3	-0.011	0.164	0.297
El_9	14196.8	0.089	0.164	0.23
El_10	16015.8	0.053	0.164	0.299

Table 3 : GLCM features on WMG-BCDSDTM of Elephant Textures.

	Average contrast	Average correlation	Average energy	Average homogeniety
C_1	76237.0	-0.047	0.165	0.433
C_2	52556.8	-0.051	0.164	0.422
C_3	107235.9	-0.038	0.166	0.462
C_4	77115.16	0.047	0.165	0.432
C_5	69522.79	-0.062	0.165	0.413
C_6	70546.15	-0.047	0.182	0.444
C_7	42989.83	-0.056	0.165	0.413
C_8	44555.19	-0.069	0.166	0.415
C_9	55080.92	-0.054	0.164	0.415
C_10	78811.38	-0.016	0.165	0.403

Algorithm 1: Texture classification algorithm based on GLCM features on WMG-BCDSDTM.

Algorithm 1

Begin

if ((contrast >=1000 && contrast <=17000) && homogeneity ==0.2)

print (" Elephant Texture");

else if ((contrast >17000 && contrast <=45000) && homogeneity ==0.3)

print(" Water Texture ");

else if ((contrast > 45000 && contrast <=150000) && homogeneity==0.4)

print(" Car Texture ");

End

Based on the algorithm the classification rates of the above images are given in Table 4 and also represented in the form of bar graph in Fig. 14.

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Table 4 : Classification rates of WMG-BCDSDTM method.

Texture Database	Classification rate of WMG-BCDSDTM (%)
Car	*80*
Water	*90*
Elephant	*90*
Average Classification rate	*86.6*

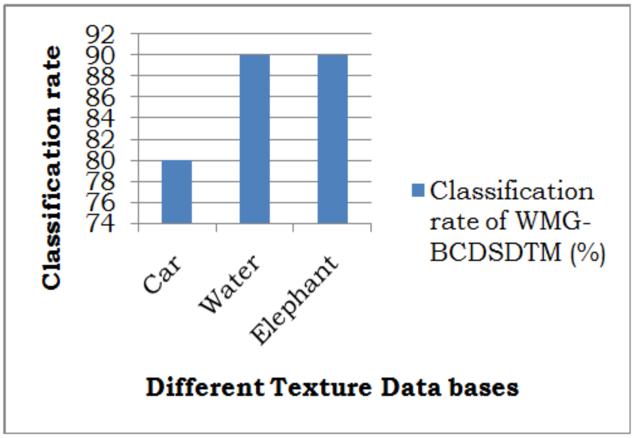

Figure 14 : Bar graph representation of Classification rates on texture databases.

VI. Conclusion

The proposed Wavelet based Morphological Gradient BCDSDTM is based on CDTM. It reduced the overall dimension of the proposed texture matrix from 81x81 as in the case of CDTM and 16x16 as in the case of Binary CDTM into 6x6. Thus it has reduced lot of complexity. Another disadvantage of the CDTM and BCDTM is it forms 16 different CDTM's for the same texture. The proposed WMG-BCDSDTM overcomes this by representing the four texture elements in the form of a 2x2 grid and deriving shape descriptors on them. The morphological gradient of the present method preserves the shape and boundaries. The proposed WMG-BCDSDTM proves that the WMG-BCDSDTM can be used effectively in wavelet domain and it reduces lot of complexity. The proposed method can also be used in image retrieval system.

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