UNSUPERVISED TEXTURE CLASSIFICATION

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ABSTRACT

We propose a novel unsupervised classification model which combines colour and texture features. Each feature is associated to a so called feature vector, where a colour fuzzy texture spectrum is defined using only the corresponding feature. It interacts with each feature vector and provides the unsupervised texture classification based on the combination of different features. The model is quite generic and isn't restricted to a particular texture feature. Herein we tested this algorithm using other texture features. Furthermore, the proposed algorithm automatically estimates the number of classes. The proposed approach gives good accuracy when compared with other methods.

Keywords: *Unsupervised classification mode, texture classification, texture model, texture spectrum*

1. INTRODUCTION

Texture plays an important role in low level image analysis and understanding. Its potential application range has been shown in various areas such as analysis of remote sensing images, industrial monitoring of product quality, medical imaging, and recently, content-based image and video retrieval. There is no formal or unique definition of texture, making texture analysis a difficult and challenging problem.

Texture features characterize the statistical or structural relationship between pixels, and provide measures of properties such as contrast, smoothness, coarseness, randomness, regularity, linearity, directionality, periodicity, and structural complexity. Image clustering or classification is one crucial step for image analysis [1]. Using statistical approaches, several schemes have been suggested right from Co-occurrence matrix, run length matrix based, auto correlation, auto regression, MRF based, moments based etc. as found in literature [4 -7], [11]. Radius and angular histogram features obtained by computing Discrete Fourier Transform of the texture image signal was used for content based image retrieval [18]. A texture representation is designed which is invariant to any geometric transformation that can be locally approximated by a sparse set of affine models [10].

In structural approach, the texture region is defined to have a constant texture if a set of local statistics or other local properties of the image are constant, slowly varying or approximately periodic. An image texture is described by the number and types of its (tonal) primitives and the spatial organization or layout of the primitives. Textures could be rated as coarse, micro, macro, regular, periodic, aperiodic, directional, random, or stochastic [18]. Texture images are analyzed by identifying the local and global properties of the images under consideration. Very few schemes have been suggested which attempt to propose for both local and global descriptors. One such method is texture spectrum scheme [8]. Gabor filters have been recently used for the texture analysis at different tuning parameters [15]. Wavelet based features have been successfully employed for the texture classification [16]. A new statistical model based wavelet domain single value decomposition for image texture classification has been described [17]. Each method discussed above can be chosen based on the application and the problem domain.

Other recent approaches for texture analysis and synthesis may be referred from [3, 9, 10, 12]. A set of texture primitives are proposed for local description and the frequency of occurrences of these primitives over the entire image is the texture primitive spectrum which is a global descriptor. The proposed primitives are tested for the presence of texture by a suitable statistical test [2].

The objective of this paper is to use the proposed local and global descriptor for texture description for performing unsupervised classification. The efficacy of the proposed method has been compared with texture spectrum approach [8]. Our proposed method has been successful because (i) the number of texture features is less and (ii) the time complexity of the proposed method for classification is lesser compared to the texture number scheme. This paper is organized as follows. This paper is organized as follows. Second section explains the methodology. In the third section, the procedure for obtaining the global texture descriptor with the proposed set of primitives is presented. Texture classification scheme has been explained and the classification results are presented in fourth section. Finally, the conclusion about our approach is presented in section 5.

2. PROPOSED METHODOLOGY

2.1 TEXTURE UNIT

The basic concept is that a texture image can be decomposed into a set of essential small units called texture units. A texture unit is represented by eight elements, each of which has only three possible values {0, 1, 2 ,3 ,4 and 5} obtained from a neighborhood of 3 x 3 image region. Here, eight elements can be ordered differently. If the elements are ordered clockwise as shown in Figure 1, the first element may take eight possible positions from the top left (a) to middle (h).

a	b	c
h		d
g	f	e

Figure 1 Texture Unit

Given a neighborhood of 3 x 3 pixels denoted by a set of nine elements: v = {v_0, v_1… v_8} where v_0 represents the intensity value of central pixel and v_1,v_2,…v_8 are the intensity values of eight neighboring pixels. Then, the corresponding texture unit can be represented as a set containing the elements, TU= {E_1,E_2,…E_8}. In Base5, the following equation (1) can be used determine the elements, E_i of texture unit.

$$E_i = \begin{cases} 0 & \text{if } v_i < v_o \text{ and } v_i < x \\ 1 & \text{if } v_i < v_o \text{ and } v_i > x \\ 2 & \text{if } v_i == v_o \text{ for } i=1,2,3,..8 \\ 3 & \text{if } v_i > v_o \text{ and } v_i > y \\ 4 & \text{if } v_i > v_o \text{ and } v_i < y \end{cases} \quad (1)$$

here x,y are user-specified values.

2.2 FUZZY TEXTURE UNIT (BASE 5)

Greater or lesser quantities are further quantized using fuzzy logic based approach as follows. Here, two more levels of comparison are introduced. The rationale behind the equation 2 is to reduce the total range of texture numbers, retaining the textural representative information. The texture number representation is shown in Figure 2.

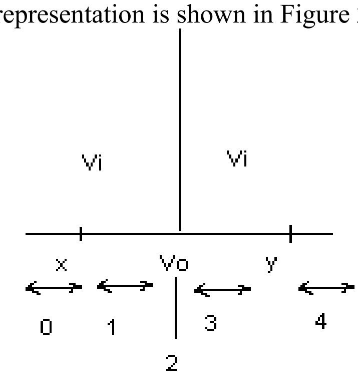


Figure 2 Texture Number (Base5) Representation

2.3 FUZZY TEXTURE NUMBER (BASE5)

The fuzzy Texture number is computed in Base5 as given in equation 2

$$FT_{nu5} = \sum_{i=1}^{8} E_i * 5^{(i-1)/2} \qquad (2)$$

The total texture numbers range from 0 to 2020.

For example, $\Longrightarrow$

$$\begin{pmatrix} 90 & 130 & 145 \\ 160 & 140 & 200 \\ 100 & 140 & 250 \end{pmatrix} \qquad \begin{pmatrix} 0 & 1 & 3 \\ 4 & & 4 \\ 0 & 2 & 4 \end{pmatrix}$$

3 x 3 neighborhood — Fuzzy Texture Unit

TU= {0, 1, 3,4, 4, 2, 0, 4}

FT_{nu5} = 1292.

3. COLOUR FUZZY TEXTURE SPECTRUM

As per our method, for the quantification of colour textures locally, a fuzzy texture unit concept is extended. Here, I used the colour model RGB. In RGB, which is popularly used, three colour planes are individually treated, as if, they are monochrome images and the features are combined to yield better representation for colour images.

Color image consists of three layers Red, Green and Blue (RGB). The color composition could be represented in a RGB space, as in Figure 3. From the RGB space, we can see that any color is a combination of red, green and blue elements. A basic color image could be described as threelayered image, with each layer as red, green and blue. When we consider a particular area of a color image, it could have different color combinations with respect to other areas of the image. An area with yellow would have a combination of red and green color elements only. Similarly, an area with magenta would have combination of red and blue elements only. Thus, the object is best described in red and green layers, not in blue layer. Hence, certain features are unique and distinct to each color layer for a particular image, depending on the color composition. RGB is frequently used in most computer applications, since, no transform is required to display information on the screen. For this reason, it is commonly the base colour space for most applications.

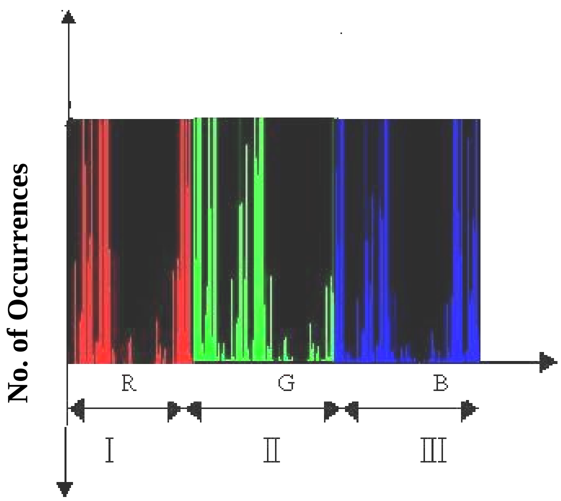


Figure 3 General Representation of a Colour Texture Spectrum in RGB colour model

In order to evaluate the performance of the colour fuzzy texture spectrum in texture characterization, several experimental studies have been carried out on VisTex Colour Texture Images. The image in Figure 4 (Fabric00069) is selected because they broadly resemble parts of remotely sensed images and they are of size128 x 128.

If Texture number scheme (Base3) is extended for the Colour image in the manner it is described above, this requires the feature vector of size 3x 6561=19683 texture numbers, which is again high to lead heavy computational requirements. To avoid that, we are using Base 5 approache. The corresponding Colour Fuzzy Texture Spectrums in RGB Colour model for Base5 is shown in Figures 5

Figure 4 Colour Texture Image Fabric00069 of size (128 x 128)

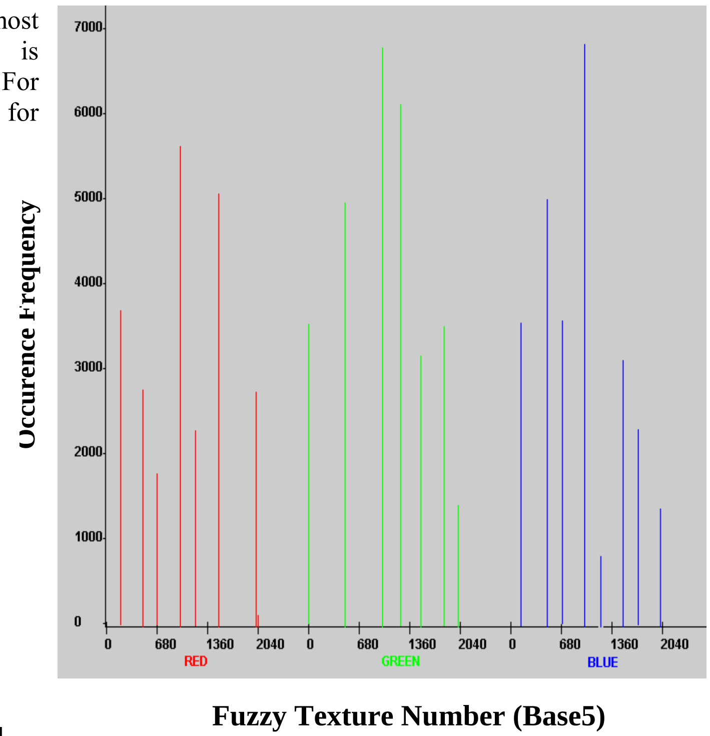


Figure 5 Colour Fuzzy Texture Spectrum in RGB (Base5) for the Image Fabric00069

4. UNSUPERVISED TEXTURE CLASSIFICATION

The second major approach to image classification is the unsupervised clustering of image data, where no prior information is required. Clustering analysis is viewed as a process of partitioning an image into groups, such that, patterns belonging to the same group are more similar to each other than are patterns belonging to different groups. The quality of texture classification depends a lot on discriminating ability of the image features used in the classification.

This section explains unsupervised classification obtained with a small database containing 180 texture image regions derived from 12 different texture images of Brodatz (1966) and VisTex (1995), Outex (1999) and Sowerby (2002) texture Album. Cluster analysis is viewed as a process of partitioning an image into groups, such that, patterns belonging to the same group are more similar to each other than patterns belonging to different groups.

4.1 UNSUPERVISED TEXTURE CLASSIFICATION WITH THE PROPOSED SCHEME

Cluster as an aggregation of two points in the test space, such that, the distance between any two points in the test space in the cluster is less than the distance between any point in the cluster and any point not in it. Here, minimum distance rule was employed and the absolute difference between two colour fuzzy texture spectra has been taken as the distance between them. The user will first supply the number of clusters desired (K) and initial threshold T. The best value of K is the minimum between cluster distances, such that, a new cluster will be created once the minimum distance between a pattern and all cluster centers is greater than T, and that the final number of clusters will be close or equal to the user defined number (K).

Algorithm

Input : Colour Texture image of Size N x N.

Output : Classified image

Step 1 : Convert the Original Colour image into Fuzzy texture unit image: that is scan the whole image using a 3 x 3 matrix (of R or G or B).

Step 2 : Input initial parameters, including the desired number of classes (K), a threshold value (T) and a step value (ΔS).

Step 3 : Set the number of effective classes Nc to zero and scan the whole image using a window of size 15 x 15.

i) The first window will be chosen as the sample subimage of the first class and let Nc=1. The second window is also considered.

ii) Compute Fuzzy Texture Spectrum as per equation (3.4) for Base5 and as per equation (3.6) for Base7 scheme and store it in separate arrays. Then, calculate the integrated absolute difference between the texture spectrum of the window and the spectrum of the sample subimage is taken as the distance between them is given in equation (3)

$$D(i) = \sum_{j=0}^{(N^8-1)} \left| W_{((j))} - S_{(i,j)} \right| \qquad (3)$$

Where D(i) denotes the distance between the window W and the sample subimage. $W_{(j)}$ represents the occurrence value of the texture unit j in the window considered.

$S_{(i,j)}$ represents the occurrence value of the texture unit j in the sample subimage of class i.

iii) If the distance between the second window and the sample subimage of the first class is less than or equal to the threshold value

a) the second window will be classified to the first class , else

b)the second window will be classified to next class and assign the value of Nc=2.

iv)The process continues by scanning the rest of the image.

a) Calculate the value of D(L) i.e minimum value from D(i), i=1,2,3,…Nc., then the central pixel of the window will be assigned to the class L.

b) If D(i) > T and (Nc+1) > K, let T=T+Δs , and then the process is repeated from stepIII, else

If D(i) >T and (Nc+1)<=K, then Nc=Nc+1 and the process will continue by considering the next windows.

Step 4 : After certain iterations, this process becomes stable and the algorithm stops with the current value of Nc and T. All the pixels will be classified to one of the Nc classes. Repeat step (I) to (IV) for the other planes and arrange them in order.

5. EXPERIMENTAL RESULTS AND DISCUSSIONS

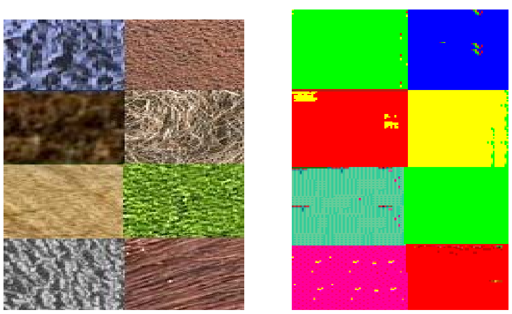
The previously described algorithm has been applied to an unsupervised textural classification over Brodatz, Vistex, Outex and Sowerby Colour Texture images. The Colour Texture Images from Vistex and Brodatz database and the Outdoor colour texture images from Outex and Sowerby are discussed and experimental results are presented in subsequent sections.

5.1 BRODATZ AND VISTEX DATABASES

The Colour Texture images are selected to form input image namely Carpet (D1), Food (D2), Sand000113 (D3), Grass (D4), Brick (D5), Deep grass (D6), Cloth (D7) and Fabric (D8). The eight textures are grouped into an image of size 125 x 252 Figure 6 (a).

The image was classified using the above-described algorithm. Figure 1.6(a) have been processed and assigned to one of the eight classes. Figure 6(b) shows the classified output result, where the different classes are represented by different pseudo colour. Eight different classes are represented by different pseudo colour. The promising result obtained shows the success of both colour fuzzy texture spectrum and classification algorithm.

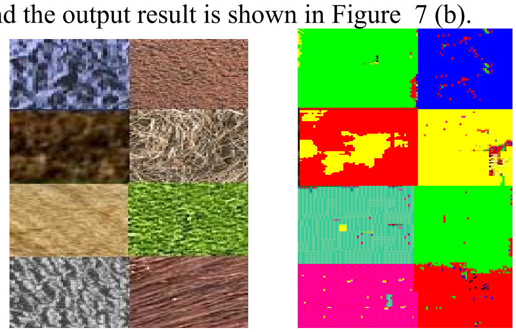
In addition to the above visual analysis of the classification result, quantitative statistics were carried out over the images, illustrated in Table 4.3. The proposed method has been also adapted for an unsupervised classification of remotely sensed multispectral image data. This algorithm provides a good recognition rate of 99.1%.



(a) (b)

Figure 6 Unsupervised Colour Texture Classification for Texture Images (Base7) consisting of Carpet (D1), Food (D2), Sand000113 (D3), Grass (D4), Brick00050 (D5), Deep grass00070 (D6), Cloth (D7) and Fabric (D8). (a) Original Image (b) Classified image

The proposed approach is compared with fuzzy based unsupervised segmentation of textured color images by Xiaoyan Dai; Maeda 2002 and the output result is shown in Figure 7 (b).



(a) (b)

Figure 7 Unsupervised Colour Texture Classification for Texture Images consisting of Carpet (D1), Food (D2), Sand000113 (D3), Grass (D4), Brick 00050 (D5), Deepgrass00070 (D6), Cloth(D7) and Fabric (D8) by Xiaoyan Dai; Maeda 2002. (a) Original Image (b) Classified image

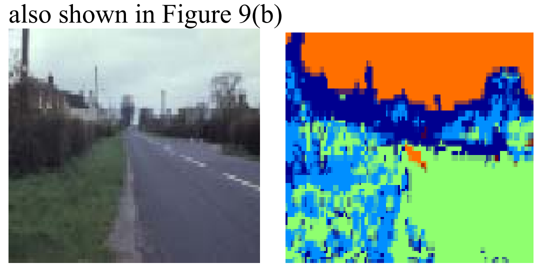
5.2 OUTEX AND SOWERBY DATABASES

In this section, we discuss the unsupervised classification of colour texture images for natural outdoor images taken from the Outex and Sowerby image databases. The Sowerby image dataset contains outdoor images taken around the Bristol area. The Outex database has two natural outdoor scene image sets: the first set contains a sequence of 22 images taken by a human walking in the park (Outex ID NS00001), and the second one contains 20 random snapshots taken outdoors (Outex ID NS00000). The target image is shown in Figure 8(a), which has been processed and assigned to one of the classes. Figure 8(b) shows the classified output result, where the different classes are represented by different pseudo colour.

(a) (b)

Figure 8 Unsupervised Colour Texture Classification for Outdoor Scene SID-06-04 (a) Original Image (b) Classified image

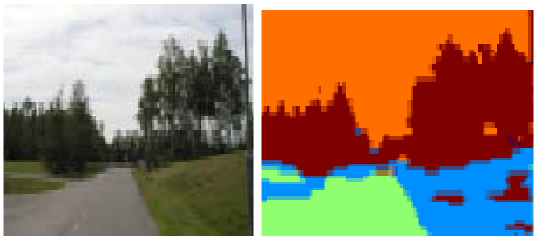
The approach is compared with a fuzzy based unsupervised segmentation of textured color images by Xiaoyan Dai; Maeda 2002. Here the test image is in Figure 9 (a) and the output result is also shown in Figure 9(b)



(a) (b)

Figure 9 Unsupervised Colour Texture classification for Outdoor Scene SID-06-04 by Xiaoyan Dai, Maeda 2002 (a) Original Image (b) Classified image

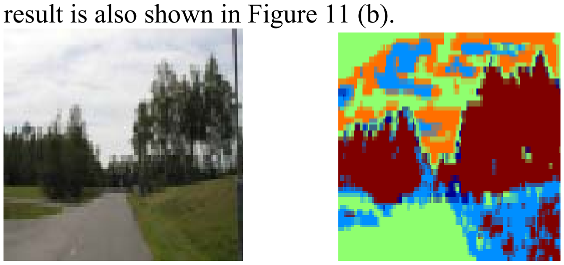
Similarly, next target image Figure 10(a) has been processed and Figure 10 (b) shows the classified output result, where the different classes are represented by different pseudo colours.



(a) (b)

Figure 10 Unsupervised Colour Texture Classification for Outdoor Scene P1010002
(a) Original Image (b) Classified image

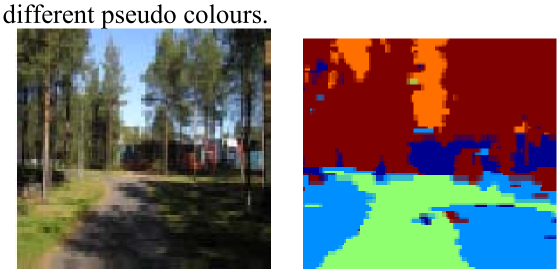
The proposed approach is compared with a fuzzy based unsupervised segmentation of textured color images by Xiaoyan Dai; Maeda, 2002. Here the test image is in Figure 11 (a) and the output result is also shown in Figure 11 (b).



(a) (b)

Figure 1.11 Unsupervised Colour Texture Classification for Outdoor Scene P1010002 by Xiaoyan Dai, Maeda 2002
(a) Original Image (b) Classified image

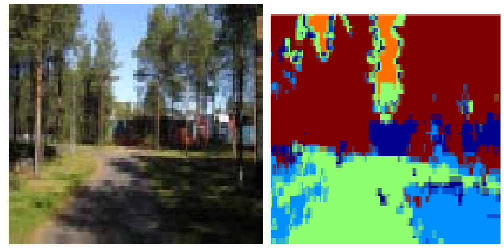
Similarly, next target input image is as shown in Figure 12(a) has been processed and Figure 12(b) shows the classified output results, where the different classes are represented by different pseudo colours.



(a) (b)

Figure 12 Unsupervised Colour Texture Classification for Outdoor Scene P91000045
(a) Original image (b) Classified image

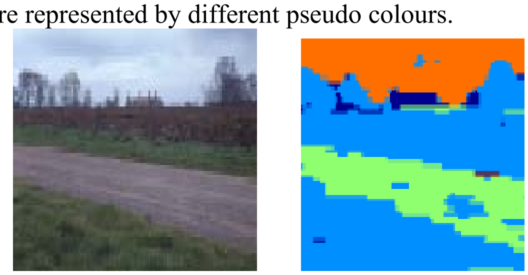
The proposed approach is compared with a fuzzy based unsupervised segmentation of textured color images by Xiaoyan Dai; Maeda, 2002. Here the test image is as shown in Figure 13 (a) and the output result is as shown in Figure 13 (b).



(a) (b)

Figure 13 Unsupervised Colour Texture Classification for Outdoor Scene P91000045 by Xiaoyan Dai, Maeda 2002
(a) Original image (b) Classified image

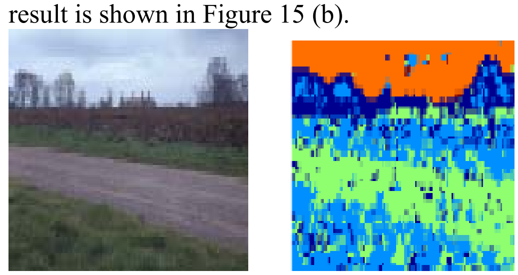
Similarly, next target input image is as shown in Figure 14(a) has been processed and different colours are assigned and represented by different pseudo colours. Figure 14 (b) shows the classified output results, where the different classes are represented by different pseudo colours.



(a) (b)

Figure 14 Unsupervised Colour Texture Classification for Outdoor Scene SID-14-07
(a) Original image (b) Classified image

The proposed approach is compared with a fuzzy based unsupervised segmentation of textured color images by Xiaoyan Dai; Maeda 2002. The test image is as shown in Figure 15 (a) and the output result is shown in Figure 15 (b).



(a) (b)

Figure 15 Unsupervised Colour Texture Classification for Outdoor Scene SID-14-07 by Xiaoyan Dai, Maeda 2002
(a) Original image (b) Classified image

6. PERFORMANCE ANALYSIS OF DIFFERENT LEVELS OF COLOUR FUZZY TEXTURE SPECTRUM FOR UNSUPERVISED TEXTURE CLASSIFICATION

This section analyses the performance of various levels of colour fuzzy texture spectrum for texture characterization and unsupervised classification. The correct classification rates Percentage for the proposed approach and work done by Xiaoyan Dai; Maeda 2002 are summarized in Table 1 and Table 2. The graphical analysis of texture classification is shown in Figure 16 and Figure 17.

Table 1 Unsupervised Classification of Colour Textures (Brodatz and Vistex Databases)

Colour Texture Image	Total No. Of Pixels	Colour Fuzzy Texture Spectrum as feature (Base7)			By Xiaoyan Dai; Maeda 2002		
		Classified Pixels	Misclassified pixels	Correct Classification %	Classified pixels	Misclassified Pixels	Correct Classification %
D1	4096	4086	10	99.75	4041	55	98.65
D2	4096	4074	22	99.46	4026	70	98.29
D3	4096	4036	60	98.53	3836	260	93.65
D4	4096	4046	50	98.77	4026	70	98.29
D5	4096	4056	40	99.02	4036	60	98.53
D6	4096	4088	8	99.8	4006	90	97.80
D7	4096	4049	47	98.85	4041	55	98.65
D8	4096	4066	30	99.26	3998	98	97.60
Average Correct Classification		99.18			97.68		

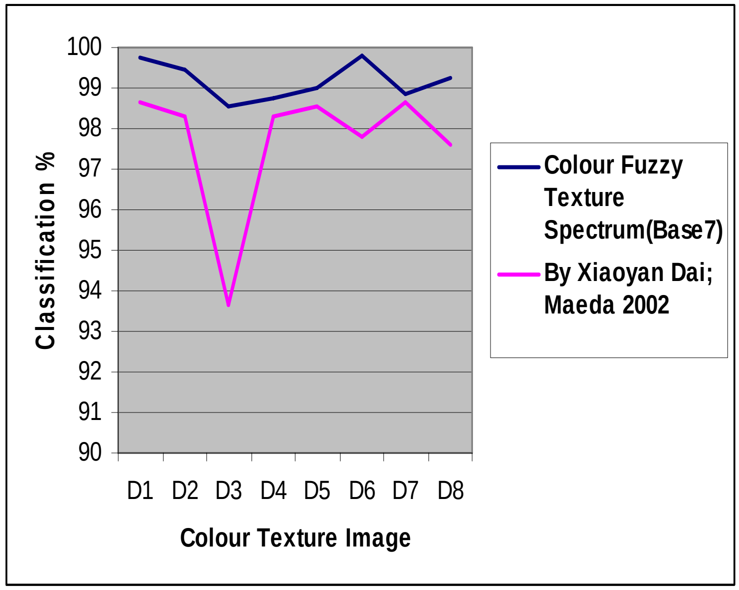


Figure 1.16 Unsupervised Texture Classification Results for different Textures – Graphical Analysis (Brodatz and VisTex Databases)

Table 2 Unsupervised Classification of Colour Textures (Outex and Sowerby Databases)

Colour Texture Image	Total No. of Pixels	Colour Fuzzy Texture Spectrum as feature (Base7)			by Xiaoyan Dai; Maeda 2002		
		Classified Pixels	Misclassified pixels	Correct Classification %	Classified pixels	Misclassified Pixels	Correct Classification %
SID-06-04	13390	13216	174	98.70	12840	550	95.89
P1010002	14016	13776	238	98.28	13248	769	94.51
P91000045	13390	13201	189	98.58	12725	665	95.03
SID-14-07	14016	13799	217	98.45	13341	675	95.18
Average Correct Classification		98.50			95.15		

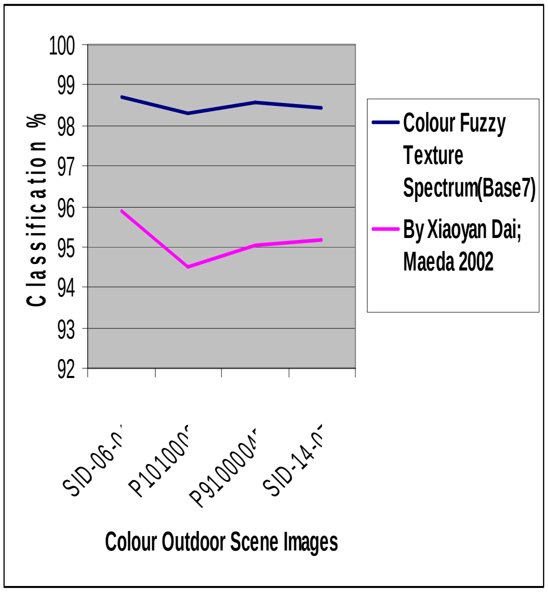


Figure 1.17 Unsupervised Texture Classification Results for different Textures – Graphical Analysis (Outex and Sowerby Database)

7. CONCLUSION

Based on the colour fuzzy texture spectrum, we have proposed an algorithm for the unsupervised textural classification of colour images. The key concept of this method is to use the colour fuzzy texture spectrum alone as the texture measure of an image. Requiring the prior information on the final classes, the algorithm will create automatically the necessary centers of classes according to the structure of the colour texture image data. This could be useful and of interest for the automatization of the textural classification of image data.

In this paper, texture classification experiments have been discussed elaborately and the performances of colour fuzzy texture spectrum have been analyzed for unsupervised texture classification and results are compared with a fuzzy based unsupervised segmentation of textured color images by Xiaoyan Dai; Maeda 2002. Using the proposed approach, an overall correct classification percentage of 99.1% is obtained for standard texture images from Brodatz and VisTex and 98.5% is obtained for standard texture images from Outex and Sowerby Databases. The work done by Xiaoyan Dai; Maeda 2002 got correct classification accuracy 97.68% for Brodatz and VisTex Album and 95.5% for Outex and Sowerby Databases. From the experimental results, it is found that when unsupervised classification is done with features, the proposed approach yields very good classification accuracy.

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