CHAPTER 4

TEXTURE CLASSIFICATION

4.1 INTRODUCTION

Brief Explanation of the proposed texture representation for colour texture images has been presented in the previous chapter. This chapter explains texture classification (both supervised and unsupervised) along with experimental justifications. Classification refers to assigning a physical object or incident into one of a set of predefined categories. In texture classification, the goal is to assign an unknown sample image to one of a set of known texture classes. Texture classification is based on a discrimination function using several texture characteristics. Texture classification can be broadly classified into two major approaches. First one is supervised classification, which is based on discrimination function using several image features. This method requires prior information about the images to be classified. The second one is unsupervised clustering of data, where no a priori information is required. In this work, the texture classification is done by using the proposed colour fuzzy texture spectrum (CFTS). The CFTS is computed by using i) base3 ii) base5 iii) base7, for the texture albums namely Brodatz, Vistex, Outex and Sowerby. This feature has been evaluated with success rate for texture characterization through several applications using Brodatz’s natural images and remote-sensed image data. It was also used with success to distinguish different lithological units from a Synthetic Aperture Radar (SAR) image.
This chapter explains both supervised and unsupervised classification obtained with a small database containing 180 texture image regions derived from 12 different texture images of Brodatz, Vistex, Outex and Sowerby texture album.

4.2 SUPERVISED TEXTURE CLASSIFICATION

Texture classification process involves two phases: the learning phase and the recognition phase. In the learning phase, the objective is to build a model for the texture representation of each texture class present in the training data. The texture content of the training images is captured with the chosen texture analysis method, which yields a set of textural features for each image. In the recognition phase, the texture content of the unknown sample is first described with the same texture analysis method. Then, the textural features of the sample are compared to those of the features of training images with a classification algorithm, and the sample is assigned to the category with the best match. The colour fuzzy texture spectrum has been evaluated from the point of view of discrimination performance. The simple discrimination method was used, and the number of mathematical operations involved was small.

The steps involved in texture training and texture classification is shown in Figures 4.1 and 4.2. In Texture training, colour fuzzy texture spectrum for the known images using the formulae given in equations 3.1, 3.2, and 3.3 are obtained and stored in features library. Using this procedure, the features of known images are computed and stored in the features library, which are further used in texture classification. The features are obtained for base3, base5 and base7 levels in RGB models.
The entire procedure for the colour texture classification is presented in the form of an algorithm below.

**Algorithm**

**Input:** Colour Texture image of Size N x N.

**Output:** Classified Image

- Creation of library of spectrums and are used as features for the known colour texture images of size N x N.
- For a target color texture image
**Step 1:** Consider a 3 x 3 image from top left corner (of R or G or B).

**Step 2:** 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.

**Step 3:** Scan through the row, leaving one column and consider next (3 x 3) as a texture unit and repeat step (II) till the bottom right corner of the image is reached.

**Step 4:** Compute the frequency of occurrences of the texture numbers. Repeat step (1) to (4) for the other two planes and arrange them in order forming the Global Descriptor as Color Fuzzy Texture Spectrum.

To create a Library, the process is repeated for as many images as required. For any candidate texture, to be classified as one of the known textures in the Library, a minimum distance criterion is used. For a texture to be classified, finds the spectrum for the known size of the image, (the Library is also created for the same size images) and the following equation (4.1) is used to classify them.

$$D(i) = \sum_{j=1}^{n} |W(j) - S(i,j)| \quad i=1,2,3,4,...$$  (4.1)

where $D(i)$: absolute difference between the Colour Fuzzy Texture Spectrum of target image and the colour fuzzy texture spectrum of a Library image $i$.

$W(j)$: occurrence value of texture unit $j$ in the texture spectrum of the window considered.

$S(i,j)$: Occurrence values of texture unit $j$ for the colour fuzzy texture spectrum of Library image $i$ and $n$ is the maximum of fuzzy texture numbers.
Finally, after finding the distances \( D(i) \) where \( i = 1, 2 \ldots \)

The target image is assigned to a class \( i \) for which \( D(i) \) is zero or minimum. Hence, the target image is classified into one of the known classes by the proposed texture representation.

### 4.2.1 Experimental Results and Discussions

In order to evaluate the performance of the Colour fuzzy texture spectrum, several experimental studies have been carried out on Brodatz, Vistex, Outex and Sowerby Colour texture images. These images are selected because they are broadly similar to one another and also, they resemble parts of remotely sensed images. The Colour Texture Images from Vistex and Brodatz database are selected and discussed in section 4.2.1.1. The Outdoor colour texture images from Outex and Sowerby are discussed and experimental results are presented in section 4.2.1.2.

#### 4.2.1.1 Brodatz and Vistex databases

Combining four Colour texture images of (A) Flowers00040, (B) food, (C) Sand000113 and (D) Bark00080 in four quadrants formed the test input image.

Using the above-described method in Base3, Figure 4.3(a) have been processed and assigned to one of the four classes. Figure 4.3(b) shows the classified output result, where the four different classes are represented by different pseudo colour. Texture classification is done with a chosen best feature and for a particular database. The classification results evident the robustness by providing high percentage of correct classification for colour textures obtained from large database. In addition to the above, visual analysis
of classification result, quantitative statistics were also carried out over the image, illustrated in Table 4.1.

![Original and Classified Images](image)

**Figure 4.3** Supervised Colour Texture Classification for Texture Images consisting of Flowers00040 (A), Food (B), Sand000113 (C) and Bark00080 (D)

(a) Original image (b) Classified image

Similarly, for Base5, the target image Figure 4.4(a) has been processed and assigned to one of the four classes. Figure 4.4(b) shows the classified output result, where the four different classes are represented by different pseudo colour.

![Original and Classified Images](image)

**Figure 4.4** Supervised Colour Texture Classification for Texture Images consisting of Flowers00040 (A), Food (B), Sand000113(C) and Bark00080 (D)

(a) Original image (b) Classified image
Similarly, for Base7, the target image Figure 4.5(a) has been processed and assigned to one of the four classes. Figure 4.5(b) shows the classified output result, where the four different classes are represented by different pseudo colour.

![Figure 4.5](image)

**Figure 4.5** Supervised Colour Texture Classification for Texture Images consisting of Flowers00040 (A), Food (B), Sand000113(C) and Bark00080 (D)

(a) Original image (b) Classified image

The approaches are compared with Texture based algorithm for color image classification by Manian Vidya et al 2000 and Colour Texture Classification using wavelet transform by Arivalagan et al, 2005 and the output results are shown in Figure 4.6 (b) and Figure 4.7 (b)

![Figure 4.6](image)

**Figure 4.6** Supervised Colour Texture Classification for Texture Images consisting of Flowers00040 (A), Food (B), Sand000113(C) and Bark00080 (D) by Manian Vidya et al 2000

(a) Original image (b) Classified image
4.2.1.2 Outex and Sowerby databases

In this section, the proposed approach is experimented with colour natural outdoor images taken from Outex and Sowerby databases. Using the above described method in Base3, the input image P9100032 from Outex database is as shown in Figure 4.8 (a) has been processed and the classified output result is as shown in Figure 4.8(b), where the different classes are represented by different pseudo colours. Texture Classification is done with the ground-truth data. The classification results evident the robustness by providing high percentage of correct classification for colour textures, obtained from large database.
The proposed approach is experimented with 50 outdoor scene images. For visual analysis of classification result, quantitative statistics are also carried out over the image, illustrated in Table 4.2.

Similarly, for Base 5, the target image as shown in Figure 4.9(a) has been processed and assigned to one of the four classes. Figure 4.9(b) shows the classified output result and the different classes are represented by different pseudo colour.

![Original image](image1) ![Classified image](image2)

**Figure 4.9 Supervised Colour Texture Classification for Colour Outdoor Scene Image P91000032**

(a) Original image (b) Classified image

Similarly, for Base 7, the target image as shown in Figure 4.10(a) has been processed and assigned to one of the four classes. Figure 4.10(b) shows the classified output result and the different classes are represented by different pseudo colour.

![Original image](image3) ![Classified image](image4)

**Figure 4.10 Supervised Colour Texture Classification for Colour Outdoor Scene Image P91000032**

(a) Original image (b) Classified image
The approaches are compared with Texture based algorithm for color image classification by Manian Vidya et al 2000 and Colour Texture Classification using wavelet transform by Arivalagan et al 2005 and the output results are shown in Figure 4.11 (b) and Figure 4.12 (b).

![Figure 4.11](image1.png)  
(a) Original image (b) Classified image  

**Figure 4.11 Supervised Colour Texture Classification for Colour Outdoor Scene Image P91000032 by Manian Vidya et al 2000**  
(a) Original image (b) Classified image

![Figure 4.12](image2.png)  
(a) Original image (b) Classified image  

**Figure 4.12 Supervised Colour Texture Classification for Colour Outdoor Scene Image P91000032 by Arivalagan et al 2005**  
(a) Original image (b) Classified image

### 4.2.2 Performance Analysis of different Levels of Colour Fuzzy Texture Spectrum for Supervised Texture Classification

This section analyses the performance of various levels of colour fuzzy texture spectrum for texture characterization and classification. Texture classification results for colour texture experiments are conducted with colour texture images. Features are extracted and stored in features library. Texture
classification is done with feature vectors and results are summarized in Table 4.1 and Table 4.2. In Table 4.2, the results of 3 more test images are added. For the sake of brevity, the test images have not been included in the thesis. The Graphical analysis of texture classification for textures is shown in Figure 4.13 and Figure 4.14.

It is noted that the above classification rates are calculated over all the pixels including the regions near the boundaries of the texture images. At these boundaries, the scanning window crosses two kinds of textures, resulting in mixed spectrum, thus, gives a lower accuracy of classification.

From the experiments conducted for texture classification with texture images using different levels and works done by Manian Vidya et al 2000 and Arivalagan et al 2005, it is observed that proposed method has good classification percentage when compared to other methods and also, the classification percentage is higher for base 7, while it is slightly less for base 5 and base3. Hence, it is concluded that when the level increases, classification percentage also increases.
Table 4.1 Supervised classification of colour texture images (Brodatz and Vistex Databases)

<table>
<thead>
<tr>
<th>Colour Texture Image</th>
<th>No. of Pixels</th>
<th>classified Pixels</th>
<th>Mis-classification Pixels</th>
<th>Correct Classification %</th>
<th>classified Pixels</th>
<th>Mis-classification Pixels</th>
<th>Correct Classification %</th>
<th>classified Pixels</th>
<th>Mis-classification Pixels</th>
<th>Correct Classification %</th>
<th>classified Pixels</th>
<th>Mis-classification Pixels</th>
<th>Correct Classification %</th>
<th>classified Pixels</th>
<th>Mis-classification Pixels</th>
<th>Correct Classification %</th>
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<tbody>
<tr>
<td>By Manian Vidya et al 2000</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>By Arivalagan et al 2005</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>97.45</td>
</tr>
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</table>
Figure 4.13 Supervised Texture Classification Results for different Textures – Graphical Analysis (Brodatz and Vistex Databases)
Table 4.2  Supervised classification of Outdoor colour texture scene images  (Outex and Sowerby Databases)

<table>
<thead>
<tr>
<th>Colour Texture Image</th>
<th>No. of Pixels</th>
<th>Base3</th>
<th>Base5</th>
<th>Base7</th>
<th>By Manian Vidya et al 2000</th>
<th>By Arivalagan et al 2005</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Classified Pixels</td>
<td>Mis-classification Pixels</td>
<td>Classified Pixels</td>
<td>Mis-classification Pixels</td>
<td>Classified Pixels</td>
</tr>
<tr>
<td>P9100032</td>
<td>13980</td>
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<td>389</td>
<td>97.21</td>
<td>13716</td>
<td>264</td>
</tr>
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<td>97.29</td>
<td>13708</td>
<td>272</td>
</tr>
<tr>
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<td>13581</td>
<td>399</td>
<td>97.14</td>
<td>13694</td>
<td>286</td>
</tr>
<tr>
<td>Test3</td>
<td>13980</td>
<td>13602</td>
<td>378</td>
<td>97.29</td>
<td>13683</td>
<td>297</td>
</tr>
<tr>
<td>Average Correct Classification</td>
<td>97.23</td>
<td>97.99</td>
<td>98.93</td>
<td>97.06</td>
<td>97.14</td>
<td></td>
</tr>
</tbody>
</table>
4.2.3 Conclusion

In this section, textures classification systems are explained in detail. From the exhaustive experimental result, obtained for texture classification for Brodatz, Vistex, Outex and Sowerby texture Albums, it is found out that when number of levels increases it improves correct classification percentage. The highest classification rate is 99.11 for level 7 for Brodatz and Vistex Texture Albums and 98.93 for level 7 for Outex and Sowerby texture Albums. It is more suitable for texture characterization and classification. Texture classification experiments have been discussed elaborately and the performances of various levels in Colour fuzzy texture spectrum have been analyzed with works done by Manian Vidya et al 2000 and Arivalagan et al 2005 for texture classification. The work done by Manian Vidya et al 2000 got Classification accuracy of 97.02% for Brodatz and Vistex albums and 97.06% for Outex and Sowerby texture Albums.
Moreover, The work done by Arivalagan et al 2005 got classification accuracy of 97.45% classification accuracy for Brodatz and Vistex albums and 97.14% for Outex and Sowerby texture Albums. It is also proved that the classification percentages for outdoor scene images are approximately equal to classification ratio of standard database textures.

The effective usage of the proposed features that are used in unsupervised Texture classification is explained in next section.

4.3 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.
4.3.1 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 (4.2)

$$ D(i) = \sum_{j=0}^{y^a-1} \left| W_{(i,j)} - S_{(i,j)} \right| $$  \hspace{1cm} (4.2) 

where $D(i)$ denotes the distance between the window $W$ and the sample subimage. $W_{(i,j)}$ 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 $N_c=2$.

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

a) Calculate the value of $D(L)$ i.e minimum value from $D(i)$, $i=1,2,3,…N_c$, then the central pixel of the window will be assigned to the class $L$. 
b) If $D(i) > T$ and $(Nc+1) > K$, let $T = T + \Delta s$, and then the process is repeated from step III. else

If $D(i) > T$ and $(Nc+1) \leq K$, 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.

### 4.3.2 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 are selected and discussed in section 4.3.2.1. The Outdoor colour texture images from Outex and Sowerby are discussed and experimental results are presented in section 4.3.2.2.

#### 4.3.2.1 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 4.15 (a).

The image was classified using the above-described algorithm. Figure 4.15(a) have been processed and assigned to one of the eight classes. Figure 4.15(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%.

![Figure 4.15](image)

**Figure 4.15** 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 4.16 (b).
4.3.2.2 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 4.17(a), which has been processed and assigned to one of the classes. Figure 4.17(b) shows the classified output result, where the different classes are represented by different pseudo colour.
Figure 4.17  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 4.18 (a) and the output result is also shown in Figure 4.18(b)

Figure 4.18  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 4.19(a) has been processed and Figure 4.19(b) shows the classified output result, where the different classes are represented by different pseudo colours.
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 4.18 (a) and the output result is also shown in Figure 4.18 (b).

Similarly, next target input image is as shown in Figure 4.21(a) has been processed and Figure 4.21(b) shows the classified output results, where the different classes are represented by different pseudo colours.
Figure 4.21 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 4.20 (a) and the output result is as shown in Figure 4.20 (b).

Figure 4.22 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 4.21(a) has been processed and different colours are assigned and represented by different pseudo colours. Figure 4.21(b) shows the classified output results, where the different classes are represented by different pseudo colours.
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 4.22 (a) and the output result is shown in Figure 4.22 (b).

4.3.3 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 4.3 and Table 4.4. The graphical analysis of texture classification is shown in Figure 4.19 and Figure 4.20.

Table 4.3  Unsupervised Classification of Colour Textures (Brodatz and Vistex Databases)

<table>
<thead>
<tr>
<th>Colour Texture Image</th>
<th>Total No. Of Pixels</th>
<th>Colour Fuzzy Texture Spectrum as feature (Base7)</th>
<th>By Xiaoyan Dai; Maeda 2002</th>
</tr>
</thead>
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<tr>
<td></td>
<td></td>
<td>Classified Pixels</td>
<td>Misclassified pixels</td>
</tr>
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<td></td>
<td>99.18</td>
<td></td>
</tr>
</tbody>
</table>
Figure 4.25  Unsupervised Texture Classification Results for different Textures – Graphical Analysis (Brodatz and VisTex Databases)

Table 4.4  Unsupervised Classification of Colour Textures (Outex and Sowerby Databases)

<table>
<thead>
<tr>
<th>Colour Texture Image</th>
<th>Total No. of Pixels</th>
<th>Colour Fuzzy Texture Spectrum as feature (Base7)</th>
<th>by Xiaoyan Dai; Maeda 2002</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Classified Pixels</td>
<td>Misclassified pixels</td>
<td>Correct Classification %</td>
</tr>
<tr>
<td>SID-06-04</td>
<td>13390</td>
<td>13216</td>
<td>174</td>
</tr>
<tr>
<td>P10100002</td>
<td>14016</td>
<td>13776</td>
<td>238</td>
</tr>
<tr>
<td>P91000045</td>
<td>13390</td>
<td>13201</td>
<td>189</td>
</tr>
<tr>
<td>SID-14-07</td>
<td>14016</td>
<td>13799</td>
<td>217</td>
</tr>
<tr>
<td>Average Correct Classification</td>
<td>98.50</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Based on the colour fuzzy texture spectrum, I 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 chapter, 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.

The effective usage of the proposed features in texture segmentation problem is explained in the next chapter.