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Texture Classification based on Fuzzy Based Texton Co-occurrence Matrix

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Abstract. The Applications of Pattern recognition like wood classification, stone and rock classification problems, the major usage techniques ate different texture classification techniques. Generally most of the problems used statistical approach for texture analysis and texture classification. Gray Level Co-occurrence Matrices (GLCM) approach is particularly applied in texture analysis and texture classification. The GLCM gives better results with accuracy but its take much time for computation. The texture analysis methods mainly depends upon how the particular texture features characterizes texture image. The accuracy of a particular texture analysis method depends what type of features are extracted from a texture image for classification, whether these features correctly classifies the textures or not. The accuracy of texture analysis method depends not only the texture features are important but also the way in which texture features are applied is also an important and significant for a critical, particular and perfect texture classification and analysis. The present paper derived a new texture analysis method i.e. co-occurrence matrix based on fuzzy rules and water shed texton patterns. The present paper applies fuzzy rules on Original texture image based on water shed texton patterns and generates Co-occurrence matrices derived a new matrix called Fuzzy based Texton Co-occurrence Matrices (FbTCoM) for texture classification. The present paper integrates the advantages of co-occurrence matrix and texton image by representing the attribute of co-occurrence matrix using water shed texton pattern based on fuzzy rule. The co-occurrence features extracted from the FbTCoM provides complete texture information about a Texture image. The proposed method is experimented on Vistex, Brodatz textures, CUReT, MAYAGAN, PBOURKE, and Google color texture images. The experimental results indicate the proposed method classification performance is superior to that of many existing methods.

Keywords: Co-occurrence Matrix, Texton, Fuzzy rule, Texture Classification

1. Introduction

Texture classification and segmentation is an important research area from industrial to bio-medical images. Basically the classification problem is identifying pragmatic texture sample from one of the several possible texture classes reliably with low computational cost for texture classification. This property implies that the choice of the textural features should be as compressed as potential and yet as sharp as potential. In other words, the texture features should give efficient complete information about the textural characteristics of the texture image. The ultimate goal of texture characterization systems is to recognize different textures. For texture classification effective algorithm is essential to discover a set of texture features with good discriminating power is needed for designing a method. Previously a number of different texture analysis methods have been introduced namely statistical, structural, transform based and model based methods [1, 2, 3] Normally textures are studied through statistical and syntactical methods. The statistical method measures the coarseness and the directionality of textures in terms of averages on a window of the image [4, 5, 6]. On the other hand syntactical method describes the shape and distribution of the entities. The statistical method has the main features which are to be extracted that includes the autocorrelation function, Fourier transform texture analysis methods, Hidden Markov random field models for classification, local linear transformation methods, power spectra, difference gray level statistics, co-occurrence matrices and from sum and different statistics [7, 8, 9, 10, 11, 12, 13].

Initially, first order or second order statistics of textures was used for texture analysis. Haralick [6]. Weszka [14] were proposed the co-occurence matrix features for texture analysis. They were compared texture feature extraction methods based on the Fourier power spectrum, second order pixel value statistics, the co-occurrence matrices statistics and pixel value run length statistics. The co-occurrence features based methods were give good results when compare with the other existing feature extraction methods. This fact is confirmed in a study by Conners and Harlow [15]. In [16], Haralick features are obtained from wavelet decomposed image yielding improved classification rates.

S.S Sreeja Mole [17] in this method classifies the textures on a pixel basis, where each pixel is associated with textural features extracted from co-occurrence matrices that differs the pixel itself. Here the windows related with the adjacent pixels are mostly overlapping resulting the pixels can be obtained by updating values already found and the classification rate in this method is about 90%. Jing Yi Tou [18] uses both the Grey-level Co-occurrence Matrices (GLCM) and Gabor filters are for texture classification and they it becomes popular. By using this method *achieved a recognition rate of 88.52%.* Guang-Hai Liu [19] this method uses the combination of two popular techniques for texture classification; those are the Grey-level Co-occurrence Matrices (GLCM) and Textons. The preset method uses the combination of three popular methods like the Grey-level Co-occurrence Matrices (GLCM), Fuzzy rules and Textons for texture classification. This method can achieve higher classification rate compare to existing methods. The present paper derived a new co-occurrence matrix based on fuzzy based textons for texture classification. The new co-occurrence matrix is called as Fuzzy Based Texton Co-occurrence Matrix (FbTCoM)

This paper is organized as follows. In Section 2 describes the generation of FbTCoM and extraction of it's texture features. Section 3 discusses results and discussions. Conclusions are given in Section 4.

2. Generation of Fuzzy based Texton Co-occurrence Matrix (FbTCoM) and Features

Many researchers have proposed so many algorithms for extracting color, texture and other features of an image texture. Color is one of the most important and central visual characteristic. Due to this reason color histogram techniques were become popular in nature which is specified the literature. The main drawback of color histogram technique is, it does not provide any information about spatial. Significant and large quantity of texture and shape information is provided by texture patterns. One of the patterns proposed by motifs [20] represents the image which is useful for texture analysis and classification. The proposed FbTCoM method consists of three steps which are listed below. In the first step of the proposed FbTCoM method is, if the texture image the color then the texture image is converted in to grey level image by using any HSV color model. The following section describes the RGB to HSV conversion procedure.

2. 1. RGB to HSV color model conversion

Recent literature revel various color models in color image processing. In order to extract facial image features from color image information, the proposed method utilized the HSV color space. In the RGB model, images are represented by three components, one for each primary color – red, green and blue. Hue is a color attribute and represents a dominant color. Saturation is an expression of the relative purity or the degree to which a pure color is diluted by white light. HSV color space describes more accurately the perceptual color relationship than RGB color space because it is adopted with a non-linear transform. The present paper has used HSV color space model conversion, because the present study is aimed to classify the human age in to four groups with a gap of 15 years.

HSV color space is created by Hue (H), saturation (S) and value (V). Hue is the property of color such as red, green and blue. Saturation is the intensity of a specific color. Value is brightness of a specific color. However, HSV color space separates the color into three categories i.e. hue, saturation, and value. Separation means variations of color are observed individually.

The transformation equations for RGB to HSV color model conversion is given below.

$$V = \max(R, G, B) \tag{1}$$

$$S = \frac{V - \min(R,G,B)}{V} \tag{2}$$

$$H = \frac{G-B}{6S} \quad if \quad V = R \tag{3}$$

$$H = \frac{1}{3} + \frac{B-R}{6S} \quad if \quad V = G \tag{4}$$

$$H = \frac{1}{3} + \frac{R-G}{6S} \quad if \quad V = B \tag{5}$$

Where the range of color component Hue (H) is [0,255], the component saturation (S) range is [0,1] and the Value (V) range is [0,255]. In this work, the color component Hue (H) is considered as color information for the classification of facial images. Color is an important attribute for image processing applications.

2. 2. Fuzzy based Texton Matrix detection

The texton patterns are defined as a set of blocks or sub windows which represent patterns sharing a common property all over the image [21, 22]. There are many types of texton patterns in texture images. In this paper, we only define four special types of water shade texton patterns and co-occurrence matrix derived from the water shed texton pattern image for texture analysis. The four water shed texton patterns are defined over a 2×2 sub image, each depicting a distinct sequence and difference between the adjacent pixels gray value must be greater than or equal to 10, as shown in Fig.1. In Fig.1, the four water shed texton patterns are denoted as C, IU (Inverted U), IC (Inverted C), and U respectively. The pixels values in each grid will form a water shed area shown in figure 1. Water shed area means water will preserved in that area. The Reverse directions of the water shed patterns are also considered. So, a total of 8 patterns are considered. The first four patterns of a 2×2 grid are shown in Fig. 1.

The proposed method utilized eight texton patterns on a 2×2 grid as shown in Fig.2. In Fig.2, the four pixels of a 2×2 grid are denoted as V1, V2, V3 and V4. If four pixels are form water shed texton pattern shown in Fig.1 and difference between V1, and V2 , V2 and V3 and V3 and V4 must be greater than or equal to 10 then the grid will form a texton. The four texton types denoted as C, IU (Inverted U), IC (Inverted C), and U respectively. A fuzzy rule is applied for these texton patterns for the construction of fuzzy based texton matrix (FBTM).

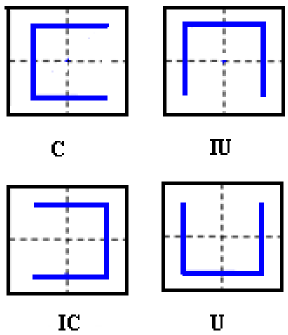
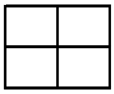


Fig.1: Four water shed patterns of a 2×2 grid

V_1	V_2
V_3	V_4

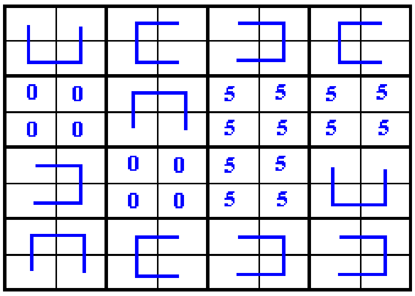
Fig.2: 2×2 grid

Fuzzy rule: If 2×2 grid has same grey levels then fuzzy value in FBTM is 0, If 2×2 grid grey values will from C pattern then fuzzy value is 1, If 2×2 grid grey values will from U pattern then fuzzy value is 2, If 2×2 grid grey values will from IC pattern then fuzzy value is 3, If 2×2 grid grey level values will from IU pattern then fuzzy value is 4 otherwise fuzzy value is 5. So, FBTM has the values from 0 to 5. The construction mechanism of fuzzy based texton matrix for the proposed method is illustrated in Fig.3. In FBTM the original size of image is reduced to half without losing any information. For example if the image size is 256×256, it will produce 128×128 FBTM. This process is called reduction step.



127	179	165	147	127	139	155	137
139	159	172	187	179	159	172	197
169	169	149	173	168	168	127	154
169	169	137	202	136	125	135	147
137	149	152	152	152	154	68	119
193	179	152	152	154	152	83	102
169	193	168	193	172	187	137	149
147	212	136	125	234	212	193	179

(a) (b)



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

(c) (d)

Fig.3: Illustration of the FBTM process: (a) 2×2 grid (b) Original image (c) texton types (d) FB Texton Matrix (FBTM).

In above figure 3b represent subpart of the facial image. In that sub part, the first 2×2 window pixels are denoted by V_1 = 127, V_2=179, V_3= 193, V_4= 159 and that window will form U pattern because the difference between V_1 and V_2 is greater than 10 and difference V_2 and V_3 is also greater than 10 and the difference between V_3 and V_4 is also greater than 10. The same window will also form Inverted C (IC) pattern but we cannot consider IC pattern because we consider only grey level values either ascending and descending order only. The first window represents only C pattern which is in ascending order and corresponding fuzzy value for C pattern is 2. The first 2×2 window is replaced with fuzzy value 2 and automatically first 2×2 window is reduced to first 1×1 window. The same procedure is applied for reaming sub windows. From that the first 8×8 sub part is reduced to 4×4 widow. Thus overall dimensionality is reduced to half.

2. 3. Co-occurrence matrix generation and extraction of its features

Recently, Guang-Hai et al. [27] proposed a Texton Co-occurrence matrix for image retrieval purpose. It gives higher retrieval rate. TCM can represent the spatial correlation of texton patterns, and it can distinguish color, texture and shape features concurrently. The generation of TCM is a computationally expensive procedure. To overcome this, the present paper considers Fuzzy based Texton Matrix (FbTM), which is directly obtained from the original image. To extract precise texture features, the present study computes co-occurrence matrix for FbTM. This overcomes the disadvantages of TCM because the size of the matrix is reduced to half.

Co-occurrence matrix can measure the properties of the texture image because co-occurrence matrices are typically large and sparse. GLCM is proposed by Haralick et al 1973 [6]. It is then widely been used for various texture analysis applications, such as texture classification [24], rock texture classification, wood classification and etc. GLCM is a popular statistical technique for extracting textural features from different types of images. In order to find the spatial relationships effectively, the classification method is used and GLCM. It is the one of the most widely used technique to measure the statistical features of a texture image. The idea of GLCM technique is to consider the relative frequencies for which two adjacent pixels are separated by a distance on the image. The GLCM collects information about pixel pairs instead of single pixels that's why this procedure is called second-order statistics.

The GLCM is generated by cumulating the total numbers of grey pixel pairs from the images. Each GLCM will be generated by defining a spatial distance d and an orientation, which can be 0^0, 45^0, 90^0 or 135^0 at a selected grey level G. The GLCM produced will be of size G × G. When the GLCM is constructed, $C_d(r,n)$ represents the total pixel pair value where r represents the reference pixel value and n represents the neighboring pixel value according to the spatial distance and orientation defined. Co-occurrence matrix is generated from the FbTM is called Fuzzy based Texton Co-occurrence Matrix (FbTCoM). Based on this, FbTCoM with different orientations 0^0, 45^0, 90^0, and 135^0 are formed as shown in Fig.4(a)-(e) respectively. Textural features are extracted from the FbTCoMs for classification process. There are a total of fourteen features for GLCM [25]. The textural features used in this method are energy, entropy, contrast, local homogeneity, correlation, shown in Eq (6) to Eq (11) [5].

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

(a)

0^0	0	1	2	3	4	5
0	2	2	0	1	2	1
1	2	2	3	4	2	1
2	0	3	4	0	0	2
3	1	4	0	4	0	2
4	2	2	0	0	2	1
5	1	1	2	2	1	4

(b)

45^0	0	1	2	3	4	5
0	0	0	1	0	0	0
1	0	0	0	1	0	0
2	1	0	2	0	0	0
3	0	0	0	0	2	0
4	0	1	0	0	1	1
5	0	0	0	0	0	0

(c)

90^0	0	1	2	3	4	5
0	0	0	0	0	0	0
1	0	1	0	0	2	0
2	0	0	0	0	0	0
3	0	2	0	1	0	0
4	0	0	0	0	0	1
5	0	1	0	0	0	0

(d)

135^0	0	1	2	3	4	5
0	0	0	1	1	0	0
1	0	0	0	1	0	1
2	1	0	2	1	1	0
3	1	1	1	0	0	0
4	0	0	1	0	0	2
5	0	1	0	0	0	0

(e)

Fig. 4: a) FB Texton matrix (b) (c), (d) and (e) represents the co occurrences on FBTM of 0^0, 45^0, 90^0 and 135^0.

$$\text{Entropy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij} \tag{6}$$

$$\text{Energy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})^2 \tag{7}$$

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij}\,(i-j)^2 \tag{8}$$

$$\text{Local Homogenity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \tag{9}$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij}\,\frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{10}$$

$$\text{Inertia} = \sum_{i,j=0}^{N-1} (i-j)^2\, P(i,j) \tag{11}$$

3. Results and Discussions

The present paper carried out the experiments on two Datasets. The Dataset-1 consists of four types of stone images i.e. Brick texture images, Granite texture images, Marble texture images and Mosaic texture images with resolution of 256×256 collected from texture databases Vistex, Brodatz, Mayang database and also from natural photographs taken by a digital camera. Some of the textures in Dataset-1 are shown in the Fig. 5. The Dataset-2 consists of four types of stone images i.e. Brick texture images, Granite texture images, Marble texture images and Mosaic texture images with resolution of 256×256 collected from texture databases like Brodatz textures, Outext texture database, CUReT, Paulbourke color textures database and also from natural texture photographs taken by a digital camera. Some of textures in Dataset-2 are shown in the Fig. 6. Dataset-1 and Dataset-2 contains 80 and 96 original color texture images respectively.

Fig.5: Input texture group of 8 samples of Brick, Granite, Mosaic., Marble with size of 256×256

Each texture image is subdivided into 16 sub images of non-overlapped image regions of size (64×64). Thus Database-1 consists of 1280 sub image regions and Database-2 consists of 1536 sub image regions and totally of 2816 image regions are available from two Databases. The classification is done for all sub texture regions derived from each texture sub image in Dataset-1 and Dataset-2.

To classify the relevant textures, extract the features in both Datasets and it is called training feature vector and extract the features of test data textures and this set is called test feature vector. Calculate the absolute difference between the training vector and the test vector. For classifying the relevant texture classes, fix a threshold value and K-*nn* classifier is used to measure the similarity between query texture and the training database textures. In case of fixed threshold, the threshold values are computed for different query textures.

The best threshold value is chosen as the threshold of that particular texture feature. The Euclidean distance between these FVs helps in classifying the texture into correct group. The results from two datasets are obtained in Table 1a , 1b & 2a, 2b which shows the average classification rates of the proposed FbTCoM method.

Fig.6: Input texture group of 8 samples of Brick, Granite, Mosaic, Marble with size of 256×256

Table 1a: Database-1: (%) mean classification rate of Brick and Marble of stone textures

Sno	Texture Name	Classification Rate	Texture Name	Classification Rate
1	Brick1	96.75	marble1	95.45
2	Brick2	92.81	marble2	97.47
3	Brick3	90.34	marble3	95.12
4	Brick4	96.28	marble4	96.58
5	Brick5	97.47	marble5	91.78
6	Brick6	96.9	marble6	87.57
7	Brick7	90.92	marble7	93.65
8	Brick8	92.71	marble8	93.78
9	Brick9	91.29	marble9	97.42
10	Brick10	96.62	marble10	87.53
11	Brick11	94.74	marble11	95.86
12	Brick12	93.17	marble12	91.79
13	Brick13	91.71	marble13	95.89
14	Brick14	92.76	marble14	95.67
15	Brick15	91.76	marble15	91.17
16	Brick16	93.37	marble16	96.37
17	Brick17	91.76	marble17	90.22
18	Brick18	91.79	marble18	96.23
19	Brick19	91.71	marble19	95.53
20	Brick20	91.76	marble20	91.75
Average		93.331		93.8415

Table 1b: Database-1: (%) mean classification rate of Granite and Mosaic of stone textures

Sno	Texture Name	Classification Rate	Texture Name	Classification Rate
1	granite1	91.51	mosaic1	93.87
2	granite2	91.72	mosaic2	90.38
3	granite3	99.68	mosaic3	97.33
4	granite4	87.56	mosaic4	91.76
5	granite5	90.81	mosaic5	89.73
6	granite6	95.56	mosaic6	97.19
7	granite7	79.29	mosaic7	83.37
8	granite8	83.34	mosaic8	91.77
9	granite9	90.53	mosaic9	95.98
10	granite10	96.27	mosaic10	94.71
11	granite11	91.72	mosaic11	98.24
12	granite12	99.74	mosaic12	96.91
13	granite13	97.62	mosaic13	97.52
14	granite14	91.75	mosaic14	92.74
15	granite15	96.93	mosaic15	97.63
16	granite16	97.19	mosaic16	97.48
17	granite17	98.23	mosaic17	91.91
18	granite18	96.83	mosaic18	97.24
19	granite19	91.85	mosaic19	91.56
20	granite20	91.78	mosaic20	97.64
		94.248		94.248

Table 2a: Database-2: (%) mean classification rate of Brick and Marble of stone textures

Sno	Texture Name	Classification Rate	Texture Name	Classification Rate
1	Brick1	92.9	marble1	93
2	Brick2	98.13	marble2	91.7
3	Brick3	93.63	marble3	91.65
4	Brick4	95.37	marble4	94.17
5	Brick5	93	marble5	94.13
6	Brick6	93.57	marble6	89.53
7	Brick7	96.13	marble7	97.53
8	Brick8	94.77	marble8	88.37
9	Brick9	93.07	marble9	95.37
10	Brick10	93.97	marble10	94.6
11	Brick11	93.75	marble11	87.5
12	Brick12	97.13	marble12	98.03
13	Brick13	91.25	marble13	88.37
14	Brick14	88.37	marble14	99.83
15	Brick15	88.37	marble15	96.43
16	Brick16	88.37	marble16	97.43
17	Brick17	88.37	marble17	88.37
18	Brick18	94.37	marble18	92.7

19	Brick19	97.67	marble19	88.37
20	Brick20	89.5	marble20	89.6
21	Brick21	93.5	marble21	91.75
22	Brick22	91.9	marble22	95.85
23	Brick23	95.2	marble23	92.03
24	Brick24	91.13	marble24	95.7
Average		**93.06**		**93**

Table 2b: Database-2: (%) mean classification rate of Granite and Mosaic of stone textures

Sno	Texture Name	Classification Rate	Texture Name	Classification Rate
1	granite1		mosiac1	94.3
2	granite2	93.75	mosiac2	93.53
3	granite3	91.6	mosiac3	88.37
4	granite4	94.97	mosiac4	93.5
5	granite5	88.37	mosiac5	91.45
6	granite6	88.37	mosiac6	90.8
7	granite7	93.43	mosiac7	96.83
8	granite8	88.37	mosiac8	90.17
9	granite9	96.67	mosiac9	95.53
10	granite10	93.07	mosiac10	90.2
11	granite11	94.55	mosiac11	88.37
12	granite12	93.07	mosiac12	85.45
13	granite13	95.33	mosiac13	95.23
14	granite14	94.83	mosiac14	93.37
15	granite15	90.73	mosiac15	95.23
16	granite16	93.57	mosiac16	91.7
17	granite17	93.4	mosiac17	91.7
18	granite18	90.6	mosiac18	94.43
19	granite19	89.6	mosiac19	91.7
20	granite20	92.17	mosiac20	96.65
21	granite21	98.83	mosiac21	97.33
22	granite22	91.7	mosiac22	98.13
23	granite23	92.43	mosiac23	97.43
24	granite24	96.2	mosiac24	97.33
		92.85		**93.28**

Mean classification rates for the proposed FbTCoM method and the other existing methods like Pixel Based image Classification [18] and GLCM and Gabor Filters technique [12] using K-NN classifier is shown in Table 3 which clearly indicates that the proposed FbTCoM outperforms the other existing methods Fig.7 shows the comparison chart of the proposed FbTCoM with the other existing methods of Table 3.

Table 3: Mean classification rates for the two different texture image datasets using k-NN classifier

Image Dataset	Pixel Based image Classification	GLCM and Gabor Filters	Proposed Method FbTCoM
Brodatz	90.34	88.53	96.93
VisTex	89.12	88.15	97.19
Mayang	91.23	87.08	98.23
CUReT	89.12	84.61	96.83
Paulbourke color	91.23	87.01	94.55

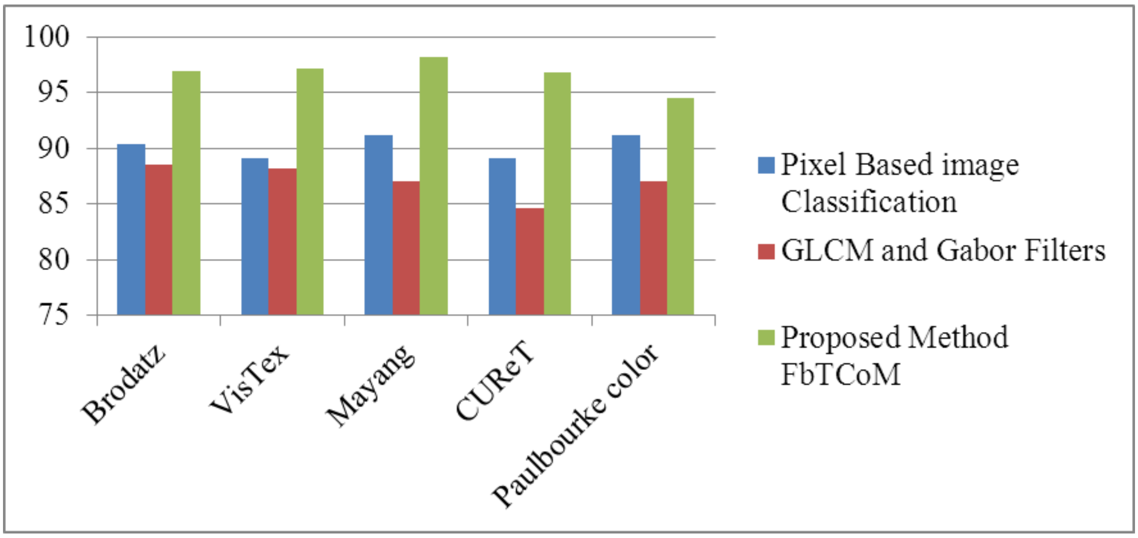


Fig.7: Classification accuracy comparison of *K-NN* classifier obtained in Brodatz VisTex, Paulbourke color, CUReT, and Mayang dataset using (K = 1, 3, 5, 7) orientations for Pixel Based image Classification, GLCM and Gabor Filters and proposed method.

4. Conclusions

The present paper derived a new co-occurrence matrix called as Matrix Fuzzy based Texton Co-occurrence Matrix (FbTCoM) for rotation invariant texture classification. Julesz proposed texton which represents the patterns of texture which is useful in texture analysis. The disadvantage of TCM is that, the computationally expensive. To overcome this problem, the present paper considered only the Texton Matrix (TM) based on fuzzy rules and water shed texton patterns, which is directly obtained from a original image and to extract a precise texture features. The novelty of the proposed method is it reduces the dimensionality of texture image while preserving the original information. So that FbTCoM gave more accurate and precise classification results. The co-occurrence matrix is generated for Fuzzy Matrices so computationally it is inexpensive. The experimental results clearly indicate the efficacy of the proposed FbTCoM over the various existing methods.

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