Image Classification Based on Centre Symmetric Fuzzy Texture Unit Matrix

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Abstract— — Texture is an important spatial feature, useful for identifying objects or regions of interest in an image. Statistical approaches have extensively studied in the texture analysis and classification. The most popular statistical methods used to measure the textural information of images are the Grey Level (GL) Co-occurrence Matrix (CM) and the Texture Spectrum (TS) Approach. The present paper combined the features of Centre Symmetric Fuzzy Texture Unit Matrix (CSFTUM) and GLCM and derived a new matrix called CSFTU-CM for texture classification. The proposed CSFTU-CM reduces the size of the TU matrix from 6561 to 67 in the case of original texture spectrum and 2020 to 67 in the case of Fuzzy Texture Spectrum (FTS) approach. Thus, it reduces the overall complexity. The co-occurrence features extracted from the CSFTU-CM provides complete texture information about an image. The experimental results indicate the proposed method classification performance is superior to that of many methods

Index Terms Texture unit, GLCM, Centre symmetric, Fuzzy texture unit. Image, Texture classification

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1 Introduction

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2 Gray Level Co-occurrence Matrix

Grey level co-occurrence matrices (GLCM) introduced by Haralick [12] attempt to describe texture by statistically sampling how certain grey levels occur in relation to other grey levels. Suppose an image to be analyzed is rectangular and has Nx rows and Ny columns. Assume that the gray level appearing at each pixel is quantized to Ng levels. Let Lx= {1,2,…,Nx} be the horizontal spatial domain, Ly= {1,2,…,Ny} be the vertical spatial domain, and G= {0,1,2,…,Ng-1} be the set of Ng quantized gray levels. The set Lx×Ly is the set of pixels of the image ordered by their row-column designations. Then the image I can be represented as a function of co-occurrence matrix that assigns some gray level in Lx×Ly; I: Lx×Ly→G. The gray level transitions are calculated based on the parameters, displacement (d) and angular orientation (θ). By using a distance of one pixel and angles quantized to 45^0 intervals, four matrices of horizontal, first diagonal, vertical, and second diagonal (0, 45, 90 and 135 degrees) are used. Then the unnormalized frequency in the four principal directions is defined by Equation (1).

$$p(i,j,d,\theta) = \# \begin{cases} ((k,l),(m,n)\epsilon\left|(L_x \times L_y) \times (L_x \times L_y)\right| \\ (k-m=0, |l-n|=d) \; or \; (k-m=d, l-n=-d) \\ or \; (k-m=-d, l-n=d) or \; (|k-m|=d, l-n=0), \\ or \; (k-m=d, l-n=d) or \; (k-m=-d, l-n=-d), \\ I(k,l)=i, \quad I(m,n)=j \end{cases} \tag{1}$$

where # is the number of elements in the set, (k, l) the coordinates with gray level i, (m, n) the coordinates with gray level j. The following Figure 1 illustrates the above definitions of a co-occurrence matrix (d=1, θ= 0^0):

3	3	3
1	3	3
1	3	2

(a)

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

(b)

450	1	2	3
1	0	0	2
2	0	0	0
3	0	0	2

(c)

900	1	2	3
1	1	0	1
2	0	0	1
3	0	0	3

(d)

1350	1	2	3
1	0	0	0
2	0	0	1
3	0	0	2

(e)

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FIGURE 1: An example of a a co-occurrence matrix

3. Derivation of Centre Symmetric Fuzzy Texture Unit Co-occurrence Matrix

The original texture spectrum approach, it contains a maximum of 6561 texture units. To reduce the number of texture units and to have high discriminating power various schemes are introduced in the literature. The FTS approach [13] uses the following Equation (2) to determine the elements, Ei of the texture unit.

$$E_i = \begin{cases} 0 & \text{if} \quad V_i < V_0 \quad \text{and} \quad V_i < x \\ 1 & \text{if} \quad V_i < V_0 \quad \text{and} \quad V_i > V_x \\ 2 & \text{if} \quad V_i = V_0 \\ 3 & \text{if} \quad V_i > V_0 \quad \text{and} \quad V_i > y \\ 4 & \text{if} \quad V_i > V_0 \quad \text{and} \quad V_i < y \end{cases} \quad \text{for } i = 1,2,3,\dots,8 \tag{2}$$

where x, y are the user-specified values. The FTU number (FTUn) is computed in Base-5 as given in Equation (3):

$$FTU_{n5} = \sum_{i=1}^{8} E_i * 5^{(i-1)/2} \tag{3}$$

The FTU numbers range from 0 to 2020.

Based on this approach, the present study derives a new scheme for the extraction of Fuzzy Texture Unit number (FTUn) called Centre Symmetric Fuzzy Texture Unit Matrix (CSFTUM). The CSFTUM approach considers a set of four connected texture elements on a 3×3 grid for evaluating the FTU instead of non-connected and corner texture elements as in the case of Cross Diagonal Texture Matrix (CDTM), and Left Right Texture Unit Matrix (LRTUM). The CSFTUM method divides the fuzzy texture information of an image by separating the neighboring pixels into a well connected four pixels of horizontal, first diagonal, vertical, and second diagonal (0, 45, 90 and 135 degrees). That is the proposed CSFTUM considers the four elements E1, E2, E3, E4 of a 3×3 neighborhood instead of 8 as shown in the Figure 2. Equation (4) derives the elements, Ei of the texture unit. This method further reduces the FTU from 2020 to 67 i.e., CSFTU values range from 0 to 66. This reduction is useful for formation of a efficient GLCM based on TU, for a good classification by reducing computational complexity.

E_1	E_2	E_3
E_8		E_4
E_7	E_6	E_5

E_1	E_2	E_3
		E_4

FIGURE 2: Representation of texture elements

The CSFTU number (FTU_n) is computed in Base-5 as given in Equation (4):

$$CSFTU_{n5} = \sum_{i=1}^{4} E_i * 5^{(i-1)/2} \tag{4}$$

The CSFTU number range from 0 to 66. An example of CSFTU with eight neighbors is shown in Figure 3.

90	95	110
97	102	115
100	105	134

2	2	1
×		2
×	×	×

CSFTU= {2, 2, 1, 2}, FTUn5 = 32

FIGURE 3: (a) Original subimage (b) Representation of CSFT elements (c) Evaluate CSFTU.

Instead of comparing each neighboring pixel with the fuzzy rule, the CSFTUM compares the center-symmetric pairs of pixels, as given in Fig.3. This method reduces the number of comparisons to half for the same number of neighbors (N=8). Compared to the original GLCM, the histogram dimension of the CSFTUM is greatly reduced.

The proposed method converts CSFTUM into CSFT-CM. The derived CSFTU-CM will be having a dimension of size 67×67. On CSFTU-CM the Haralick features such as energy, entropy, contrast, local homogeneity, correlation, cluster shade and cluster prominence are evaluated as specified in the Equations (5) to (11) respectively

$$\text{Entropy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij}) P_{ij} \tag{5}$$

$$\text{Energy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})^2 \tag{6}$$

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

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

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{9}$$

where P_{ij} is the pixel value in position (i,j) of the texture image, N is the number of gray levels in the image, μ is $\mu = \sum_{i,j=0}^{N-1} i P_{ij}$ mean of the texture image and σ^2 is $\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij} (i-\mu)^2$ variance of the texture image

$$\text{Cluster Shade} = \sum_{i,j=0}^{N-1} P_{ij} \left(i - M_x + j - M_y\right)^3 \tag{10}$$

$$\text{Cluster Prominence} = \sum_{i,j=0}^{N-1} P_{ij} \left(i - M_x + j - M_y\right)^4 \tag{11}$$

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where $M_x = \sum_{i,j=0}^{N-1} iP_{ij}$ and $M_y = \sum_{i,j=0}^{N-1} jP_{ij}$

The present method derived on CSFTU-CM, a set of Haralick features to obtain the texture information about an image. This new method combines the merits of both GLCM and CSFTUM of the texture analysis and gives complete texture information about an image. The proposed CSFTU-CM reduces the computational time complexity, because of the reduced size of the CSFTUM from 6561 to 67 as in the case of TU [15] and 2020 to 67 as in the case of FTS [14]. The entire process is furnished below in algorithm 1.

Based on the derived CSFTU-CM the present study derives an algorithm for the efficient classification of textures. The algorithm is given below.

Algorithm 1: Proposed method of Efficient Classification of images based on the derived CSFTU-CM features.

Begin

1.Take the original textures T_k, O_k, $k= 1:20$

2.Subdivide the T_k, into 16 equal sized blocks. Name them as subimage T_kS_i, $k=1: 20$ and $i = 1:16$. They are used as sample textures for testing. For classification a LOOM classifier is used as discussed in Section 4.

3.Subdivide the O_k, into 4 equal sized blocks. Name them as subimage O_kS_i, $k=1: 20$ and $i = 1:4$.

4.Select at random, a training sample subimage from each O_k, $k= 1: 20$ and denote it as O_kS_j where 'j' is any of the sample pieces 1 to 4 of a particular O_k.

5.Evaluate CSFTUM

6.Then on step(5), evaluate CSFTU-CM by moving the 3×3 matrix across the sample with overlapping (convolving) for each of the four connected neighbors.

7.Obtain Haralick features on CSFTU-CM in four directions.

8.To classify a sample image T_kS_j, absolute difference $D(k)$ is calculated from Equation (12) where $D(k)$, denotes the absolute difference between CSFTU-CM of testing and training set sample images. The tested set falls into the *Class k*, $k= 1:20$, such that $D(k)$ is minimum among all the $D(k)$, $k=1: 20$.

9.Now for each texture T_k, $k=1:20$, evaluate the classification gain (G) as given in Equation (13) and list the output in the form of table.

End

The feature vector derived from the unknown image is compared with the feature vectors in the database using the distance vector formula, given Equation (12).

$$D(i) = \sum_{j=0}^{N} [f_j(k) - f_j(i)] \qquad (12)$$

where N is the total number of features in f, i = 1 to Q (Q is the number of images in the database), $f_j(k)$ represents the jth feature of unknown texture image (k) and $f_j(i)$ represents the jth feature of texture belonging to i^{th} texture. In classification, the unknown texture is assigned to n^{th} texture image if $D(n) < D(i)$ for all i; $i \neq n$.

3.1 Leave One Out Method Classifier Technique (LOOM)

For the classification aspect training set is needed. In most scenarios, a training set is comprised of half of the entire database. LOOM consists of leaving one image from the database "out", and using all the other samples for training. After the classifier has been changed, the left out image is classified by the algorithm. The process is iterated and each image of the database is left out once. This permits the computation of the classification accuracy for the entire database,

The success of classification is measured using the classification gain (G) and is calculated using Equation (13).

$$G(\%) = \frac{C_{corr}}{M} \times 100\% \qquad (13)$$

where Ccorr is the number of sub-images correctly classified and M is the total number of subimages, derived from each texture image.

Experimental Analyses

The proposed approach is tested with a set of two databases one from the OuTex and the other Granite texture database. The OuTex dataset is composed of 45 texture classes (one image for each class) from the OuTex library [16] as shown in Figure 4. The size of the original images is 746×538 pixels. As the texture surface rotates, only the central part of the image captures the same portion of the surface. For this reason, the central part of the rotated images is retained which is calculated by $(\min(W,H)/\sqrt{2})$ where W and H are the width and height of the original images. This gives an image size of 380×380 pixels. Each image is subdivided into 16 non-overlapping sub-images, giving a database of 720 texture samples (16 for each class). The granite dataset [17] is composed of 12 granite texture classes. The overall dataset is composed of 48 images, 4 for each class as shown in Figure 5. The texture images are subdivided into smaller non-overlapping texture patches.

To evaluate the influence of the patch size on the classification procedures, three different sizes have been considered, namely, 64×64, 32×32, and 16×16. The various Haralick features such as contrast, energy, entropy, local homogeneity, cluster shade, cluster prominence and maximum probability, as suggested by Haralick et al. (1973), are calculated for the CSFTU-CM using the formulas given in Equations (5) to (11). The texture features are averaged along horizontal, vertical and diagonal directions. Given all features, the feature selection method is performed. For classification, LOOM classifier is used to guarantee strict separation of test and training set with the maximization of number of training images.

Tables I and II summarize the results obtained for each classification procedure, using the three different patch sizes. From the results, it is observed that the classification accuracy increases as the sample size increases

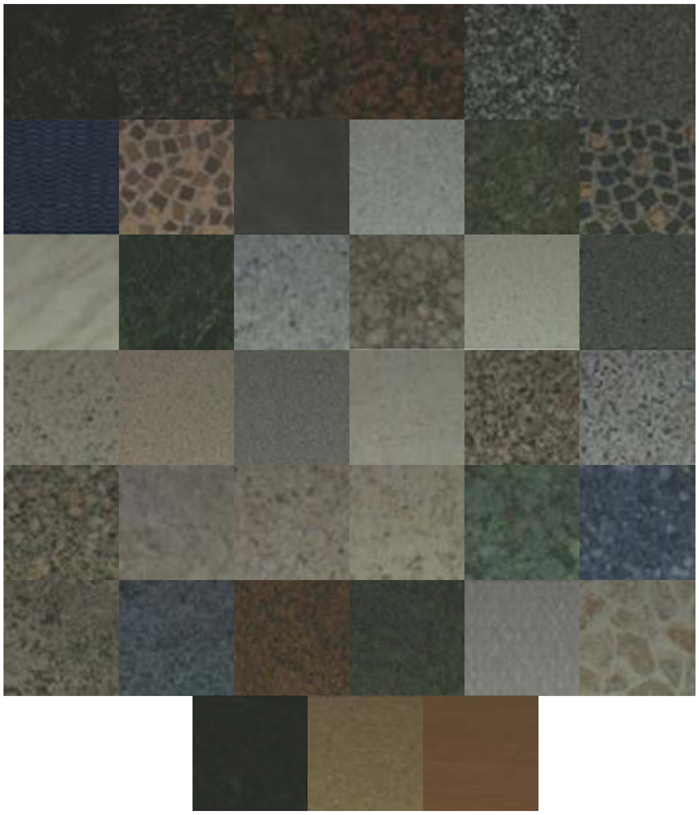

FIGURE 4: Dataset-1: 45 texture classes (one image for each class) from OuTex. Canvas{005, 021}; Carpet{005}; Granite{001, 003, 004, 005, 006, 007, 008, 009, 010}; Paper{006};Plastic{001, 002, 003, 004, 005, 009, 016, 017, 018, 019, 020, 021, 022, 023, 024, 025, 026, 027, 028, 029, 030, 031, 032, 033, 034, 035, 036, 038, 040, 041}; Wood{006, 008}.

FIGURE 5: Dataset-2: The dataset of granite textures used in the experiments (unrotated images). From the top: Acquamarina, Azul Capixaba, Bianco Cristal, Bianco Sardo, Rosa Beta, Azul Platino, Giallo Ornamentale, Giallo Napoletano, Giallo Santa Cecilia, Giallo Veneziano, Rosa Porri˜no A, Rosa Porri˜no B.

S.No	Texture Name	16×16	32×32	64×64
1	Canvas-005	95	96.7	96.9
2	Canvas-021	90.2	92.7	95.8
3	Carpet-005	90.5	92.8	95.8
4	Granite-001	91.5	91.7	95.8
5	Granite-003	91.1	97.5	97.5
6	Granite-004	91.7	91.7	95.8
7	Granite-005	91.7	95.8	91.7
8	Granite-006	91.7	97.5	92.7
9	Granite-007	83.3	91.7	97.4
10	Granite-008	79.2	91.7	97.7
11	Granite-009	83.3	89.7	99.2
12	Granite-010	91.7	91.7	95.8
13	Paper-006	95.8	93.3	96.5
14	Plastic-001	87.5	91.7	94.2
15	Plastic-002	90.8	91.7	98.2
16	Plastic-003	91.7	91.7	91.7
17	Plastic-004	91.8	91.7	93.8
18	Plastic-005	95.8	97.5	96.7
19	Plastic-009	87.5	91.5	97.5
20	Plastic-016	87.5	91.7	92.6
21	Plastic-017	91.7	91.7	96.7
22	Plastic-018	95.8	91.7	96.8
23	Plastic-019	92.5	93.5	96.4
24	Plastic-020	81.5	91.5	95.4
25	Plastic-021	91.1	93.4	97.6
26	Plastic-022	90.6	90.3	97.6
27	Plastic-023	89.9	90.6	97.4
28	Plastic-024	88	95.1	96.3
29	Plastic-025	90.4	96.2	97.1
30	Plastic-026	92.6	94.9	98.2
31	Plastic-027	92.1	97.4	96.9

32	Plastic-028	87.8	96.7	95.5
33	Plastic-029	91.8	91.8	97.6
34	Plastic-030	89.7	90.3	97.6
35	Plastic-031	90.6	94.2	96.9
36	Plastic-032	88.4	97.4	97.5
37	Plastic-033	91.1	95.9	96.2
38	Plastic-034	88.8	91.9	98.2
39	Plastic-035	92.7	92.7	96.8
40	Plastic-036	91.4	97.2	99.6
41	Plastic-038	97.7	97.6	99.7
42	Plastic-040	91.5	94.5	97.1
43	Plastic-041	91.7	93.6	96.5
44	Wood-006	91.7	91.7	94.7
45	Wood-008	93.2	92.4	98.2

TABLE 1: Percentage of correct classification on CSFTU-CM using the proposed algorithm on OuTex database with the dataset-1.

S.No	Texture Name	16×16	32×32	64×64
1	Acquamarina-1	92.1	97.4	96.9
2	Acquamarina-2	87.8	89.7	95.5
3	Acquamarina-3	91.8	93.8	97.6
4	Acquamarina-4	89.7	90.3	97.6
5	Azul Capixaba-1	90.6	96.2	96.9
6	Azul Capixaba-2	88.4	97.4	97.5
7	Azul Capixaba-3	91.7	95.9	96.2
8	Azul Capixaba-4	88.8	91.9	98.2
9	Bianco Cristal-1	92.7	92.7	96.8
10	Bianco Cristal-2	97.4	97.2	99.6
11	Bianco Cristal-3	91.7	91.7	95.8
12	Bianco Cristal-4	95.8	97.3	98.5
13	Bianco Sardo-1	90.5	91.7	94.2
14	Bianco Sardo-2	90.8	91.7	98.2
15	Bianco Sardo-3	91.7	93.7	91.7
16	Bianco Sardo-4	91.8	94.7	95.8
17	Rosa Beta-1	95.8	95.5	96.7
18	Rosa Beta-2	87.5	91.5	97.5
19	Rosa Beta-3	87.5	91.7	94.6
20	Rosa Beta-4	91.7	93.6	96.5
21	Azul Platino-1	91.7	91.7	94.7
22	Azul Platino-2	93.2	94.4	98.2
23	Azul Platino-3	90.7	92.2	96.5
24	Azul Platino-4	92.4	95.6	96.67
25	Giallo Ornamentale-1	92.1	97.4	96.9
26	Giallo Ornamentale-2	91.8	96.7	95.5
27	Giallo Ornamentale-3	91.8	92.8	97.6
28	Giallo Ornamentale-4	89.7	90.3	97.6
29	Giallo Napoletano-1	90.6	96.2	96.9
30	Giallo Napoletano-2	88.4	97.4	97.5
31	Giallo Napoletano-3	91.1	95.9	96.2
32	Giallo Napoletano-4	88.8	91.9	98.2
33	Giallo Santa Cecilia-1	92.7	92.7	96.8
34	Giallo Santa Cecilia-2	90.4	97.2	99.6
35	Giallo Santa Cecilia-3	94.7	96.6	99.7
36	Giallo Santa Cecilia-4	83.3	91.7	97.4
37	Giallo Veneziano-1	83.3	91.7	97.4
38	Giallo Veneziano-2	89.2	91.7	97.7
39	Giallo Veneziano-3	89.3	92.7	99.2
40	Giallo Veneziano-4	91.7	91.7	95.8
41	Rosa Porri˜no A-1	92.8	93.3	96.5
42	Rosa Porri˜no A-2	87.5	91.7	94.2
43	Rosa Porri˜no A-3	90.8	91.7	98.2
44	Rosa Porri˜no A-4	91.7	91.7	94.7
45	Rosa Porri˜no B-1	91.8	91.7	93.8
46	Rosa Porri˜no B-2	95.8	94.5	96.7
47	Rosa Porri˜no B-3	95.8	93.5	96.7
48	Rosa Porri˜no B-4	87.5	91.5	97.5
	Average	91	93.6	96.8

TABLE 2: Percentage of correct classification on CSFTU-CM using the proposed algorithm on Granite database with the dataset-2.

4.1 Comparison of Proposed CSFTU-CM With Existing Methods

TABLE 3: Comparison of the proposed CSCM method with the existing methods

Texture Group	CDTM	Modified CDTM	LRTUM	Proposed CSCM
OuTex	94.6	94.7	95.7	96.5
Granite	92.5	93.5	94.5	96.8
VisTex	91.8	93.5	92	94.4
Brodatz	91.3	93.5	95	95.7
Average (%) of Classification	91.5	93.8	94.3	95.8

The proposed CSFTU-CM is compared with the recent classification methods CDTM [18], Modified CDTM [19] and LRTUM [20]. Table III show the mean percentage classification rate of the proposed CSFTU-CM and existing methods. The graphical analysis of this is shown in Fig.5. From Table III and Figure 6 clearly evident that, the proposed CSCM exhibits a high classification rate than the existing methods.

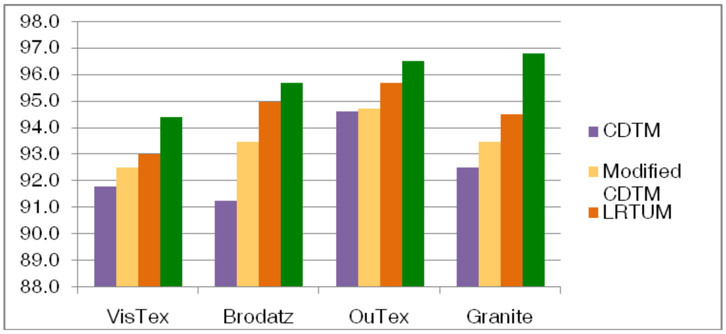

FIGURE 6: Comparative analysis of proposed CSCM with existing methods

CONCLUSIONS

The proposed CSFTU-CM reduces the size of texture unit matrix from 6561 to 67 as in the case of OTS [15] and 2020 to 67 as in the case of FTS approach [14]. This feature extraction process is quite efficient with less complexity. When compared with other approaches, the proposed scheme is more effective and exhibiting increased classification ability by using smaller feature vectors. The experimental results based on different images show that the implemented classification scheme is quite robust to noise and it is more efficient than the existing methods.

References

[1] J.S. Bridle, —Probabilistic Interpretation of Feed forward Classification Network Outputs, with Relationships to Statistical Pattern Recognition,” Neurocomputing-Algorithms, Architectures and Applications, F. Fogelman-Soulie and J. He-rault, eds., NATO ASI Series F68, Berlin: Springer-Verlag, pp. 227-236, 1989.

[2] W.-K. Chen, “Linear Networks and Systems. Belmont, Calif.: Wads-worth,” pp. 123-135, 1993.

[3] H. Poor, “A Hypertext History of Multiuser Dimensions,” MUD History, http://www.ccs.neu.edu/home/pb/mud-history.html. 1986.

[4] K. Elissa, “An Overview of Decision Theory,".

[5] R. Nicole, "The Last Word on Decision Theory," J. Computer Vision, submitted for publication.

[6] C. J. Kaufman, “Rocky Mountain Research Laboratories, Boulder,” Colo., personal communication, 1992.

[7] D.S. Coming and O.G. Staadt, "Velocity-Aligned Discrete Oriented Polytopes for Dynamic Collision Detection," IEEE Trans. Visualization and Computer Graphics, vol. 14, no. 1, 2007, pp. 1-12.

[8] S.P. Bingulac, —On the Compatibility of Adaptive Controllers,” Proc. Fourth Ann. Allerton Conf. Circuits and Systems Theory, 1994, pp. 8-16.

[9] L. Hubert and P. Arabie, “Comparing Partitions,” J. Classification, vol. 2, no. 4, 1985, pp.193-218.

[10] L. Wang and D.C. He, "A new statistical approach for texture analysis", Photogrammem'c Engineering & Remote Sensing, vol.56, 1990, pp.61-66.

[11] D.C. He and L. Wang, "Texture unit, texture spectrum and texture analysis", in Proc of IGARSS.89, Vancouver, Canada, vo1.5, 1989, pp.2769-2772.

[12] R.M. Haralick, K. Shanmugan and I. Dinstein, "Textural features for image classification", IEEE Trans. Sysr., Man., Cybern., Vol. SMC-3, 1973, pp.610-621.

[13] G.Wiselin Jiji, L.Ganesan, “A new approach for unsupervised segmentation,” Applied Soft Computing, Vol.10, 2010, pp.689-693.

[14] Aina Barcelo, Eduard Montseny, Pilar Sobrevilla, “Fuzzy Texture Unit and Fuzzy Texture Spectrum for texture characterization,” Fuzzy Sets and Systems 158, 2007, pp:239-252.

[15] D.C. He and L. Wang, "Texture features based on texture spectrum," Pattern Recognition, vol. 25, no. 3, 1991, pp.391-399,

[16] Ojala T., Pietikäinen M., Mäenpää T., Viertola J., Kyllönen J., Huovinen S., “Outex-new framework for empirical evaluation of texture analysis algorithms,” In: Proc. 16th Int. Conf. on Pattern Recognition, vol. 1, pp:701–706, 2002(b).

[17] Antonio Fern´andez, Ovidiu Ghita, Elena Gonz´alez, Francesco Bianconi, Paul F. Whelan, “Evaluation of robustness against rotation of LBP, CCR and ILBP features in granite texture classification,” Machine Vision and Applications, 2011.

[18] Abdulrahman A. AL-JANOBI and AmarNishad M. THOTTAM, “Testing and Evaluation of Cross-Diagonal Texture Matrix Method, 2001.

[19] Al-Janobi, Performance evaluation of cross-diagonal texture matrix method of texture analysis, Pattern Recognition, 34, 2000, pp:171-180.

[20] B.Sujatha, V.Vijaya Kumar, M. Chandra Mohan,” Rotationally Invariant Texture Classification Using LRTM Based On Fuzzy Approach,” IJCA, Vol.33, Iss. 4, 2011, pp: 1-5.