

# Texture Analysis and Classification Based on Fuzzy Triangular Greylevel Pattern and Run-Length Features

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## Abstract

Your Texture analysis is one of the most important techniques used in the analysis and interpretation of images, consisting of repetition or quasi repetition of some fundamental image elements. The present paper derived Fuzzy Triangular Greylevel Pattern (FTGP) to overcome the disadvantages of LBP and other local approaches. The FTGP is a 2 x 2 matrix that is derived from a 3 x 3 neighborhood matrix. The proposed FTGP scheme reduces the overall dimension of the image while preserving the significant attributes, primitives, and properties of the local texture. From each 3 x 3 matrix a Local Grey level Matrix (LGM) is formed by subtracting local neighborhoods by the gray value of its center. The 2 x 2 FTGP is generated from LGM by taking the average value of the Triangular Neighbor Pixels (TNP) of the 3 x 3 LGM. A fuzzy logic is applied to convert the Triangular Neighborhood Matrix (TNM) in to fuzzy patterns with 5 values 0, 1, 2, 3 and 4 instead of patterns of LBP which has two values 0, 1. On these fuzzy patterns a set of Run Length features are evaluated for an efficient classification. The proposed method is experimented with wide variety of textures, and exhibited with a high classification rate. The proposed FTGP with run length features shown its supremacy and efficacy over the various existing methods in classification of textures.

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**Index terms**— run length features, fuzzy triangular greylevel pattern (ftgp), triangular neighbor pixels local greylevel matrix (lgm).

## 1 Introduction

Analysis of textures is a fundamental research topic in the area of computer vision and has many potential applications, for example, in industrial surface inspection, remote sensing, and biomedical image analysis. Classification refers to as assigning a physical object or incident into one of a set of predefined categories. Many texture classification problems usually require the computation of a large amount of texture features in order to characterize their associated patterns. This implies that texture classifiers frequently combine big sets of features without taking into account their relevance and redundancy. Thus, lowering the dimensionality of a feature set is necessary for preserving the most relevant features and it reduces the computational cost derived from unnecessary features [1,2,3,34,35].

Numerous algorithms of textural features extraction have been presented during the past decades [4,5]. Textures are classified recently by various methods: preprocessed images [34], long linear patterns [35], edge direction movements [21], avoiding complex patterns [10], marble texture description [36], skeleton extraction of texture [7], long linear patterns using wavelets [8] wavelet transform [8,9,10]. and Gabor filters [11]. More recently, the local-binary-pattern (LBP) operator [12,13,14] is used for texture classification. LBP operator is a statistical texture descriptor of the characteristics of the local structure. LBP provides a unified description including both statistical and structural characteristics of a texture patch, so that it is more powerful for texture analysis. The concept of LBP is also extend in applications such as face recognition and age classification [15,16,17], industrial

visual inspection [18,19], segmentation of remote-sensing images [20], and classification of real outdoor images [21].

An efficient nonparametric methodology for texture analysis based on magnitude LBP (MLBP) [22,23,24,25,26] is recently proposed and it has been made into a powerful measure of image texture, in terms of accuracy and computational complexity in many empirical studies. To address the connectivity limitations of LBP and MLBP, we propose a matrix called Triangular Neighborhood Matrix (TNM), which generates  $2 \times 2$  texton patterns. A fuzzy member ship is introduced on TNM to extract local texture information efficiently. The present paper derived run length matrix on the proposed scheme and evaluated runlength features for efficient, precise and accurate classification of textures. A ( D D D D ) F 2012

## 2 Year

The rest of the paper is organised as follows. Section 2 describes the proposed method. Section 3 describes the results and discussions and conclusions are given in section 4. pattern (FTGP), triangular neighbor pixels local greylevel matrix (LGM).

## 3 II.

## 4 Methodology

## 5 Derivation of TNM (Triangular Neighborhood Matrix)

The present paper derived FTGP to overcome the disadvantages of LBP and other local binary approaches. Runlength features are evaluated on FGTP for a precise classification in 5 steps.

Step 1: Formation of Local Grey level Matrix (LGM):

A neighborhood of  $3 \times 3$  pixels is denoted by a set containing nine elements:  $P = \{P_1, P_1 \dots P_9\}$ , here  $P_5$  represents the intensity value of the central pixel and remaining value are the intensity of neighboring pixels as shown in Fig. 1(a). The Local Grey level Matrix (LGM) values of the neighboring pixels (LGMP<sub>i</sub>) are obtained by evaluating the absolute difference between the neighboring pixel and the gray value of the central pixel, as described by the Equation (1) as shown in Fig. 1.  $P_1 P_2 P_3$

LGMP 1  
LGMP 2  
LGMP 3  $P_4 P_5 P_6$   
LGMP 4  
LGMP 5  
LGMP 6  $P_7 P_8 P_9$   
LGMP 7  
LGMP 8  
LGMP 9

Where LGMP  $i$  is the obtained grey value of the pixel  $P_i$  of the LGM. The equation 1 demonstrates that always LGMP 5 value (central pixel value) will be always zero.

Step 2: Generation of Triangular Neighborhood Matrix (TNM) from LGM of step 1:

The  $2 \times 2$  TNM is generated from LGM by taking the average value of the Triangular Neighbor Pixels (TNP) of the  $3 \times 3$  LGM as shown in figure 3 and as given in equation 2,3, 4 and 5 . The triangular neighbors are considered because the central pixel of LGM is always zero. That is one need not necessary to consider this.?????  
 $1 = (LGMP_1 + LGMP_1 + LGMP_1) \mathbf{3}????? \quad 2 = ?LGMP_2 + LGMP_3 + LGMP_6 \mathbf{3}????? \quad 3 = (LGMP_4 + LGMP_7 + LGMP_8) \mathbf{3}????? \quad 4 = (LGMP_6 + LGMP_8 + LGMP_9) \mathbf{3}$

LGMP 1  
LGMP 2  
LGMP 3  
LGMP 4  
LGMP 5  
LGMP 6 TNP 1 TNP 2  
LGMP 7  
LGMP 8

LGMP 9 Fuzzy logic has certain major advantages over traditional Boolean logic when it comes to real world applications such as texture representation of real images. LBP patterns are formed and counted from 0's and 1's. However, the dangerous situation of LBP is that even if the difference is minimum let us say 1 or maximum i.e. 255, it converts it into 1. That is LBP treats even the difference of 1 and 255 as homogeneous. This clearly indicates the patterns of LBP will never gives totally useful and significant information. The above property misuses the power of LBP method. To address this in the proposed method fuzzy member ship is introduced. The aim of fuzzy approach in forming FTGP is to extract local texture information from TNM pixels for representing the texture information accurately. To deal accurately with the regions of natural images even in the presence of noise and the different processes of caption and digitization FTGP is introduced on TNM. For example, even if the human eye perceives two neighboring pixels as equal, they rarely have exactly the same intensity values.

The fuzzy patterns are chosen in the present paper because, recently, fuzzy based methods have been used in texture analysis and in image segmentation [28,29]. The FTGP consists of fuzzy patterns with 5 values {0, 1, 2, 3 and 4} instead of two patterns of LBP. Though the present paper considers five possible fuzzy grey level values, but at any time only a maximum of four fuzzy patterns will appear because the FTGP is a 2 x 2 matrix. In LBP binary patterns are evaluated by comparing the neighboring pixels with central pixel. The FTGP are derived by comparing the each pixel of the 2 x 2 TNM with the average pixel values of the TNM. The FTGP representation is shown in Fig. 4. The following Eqn. (??) is used to determine the elements, FTGP i of the TNM. For example, the process of evaluating FTGP from a sub TNM image of 2 x 2 is shown in Fig. 5. In this example x and y are chosen as  $v_0/2$  and  $3v_0/2$  respectively. The membership values of FTGP neighboring pixels are useful for characterization of textures. To address this difficulty the present approach derived Run length matrix (RLM) on the FTGP of the image.

## 6 Definition of the Run-Length Matrices: Galloway

proposed the use of a run-length matrix for texture feature extraction [12]. For a given texture image, a runlength matrix  $P(i; j)$  is defined as the number of runs with fuzzy value  $i$  and run length  $j$ . Various texture features can then be derived from this run-length matrix.

For a given image, the proposed method defines a RLM ( $i,j$ ) on FTGP as number of runs starting from location ( $i,j$ ) of the FTGP image. The proposed method derived five different RLM-FTGP. The RLM-FTGP 0, RLM-FTGP 1, RLM-FTGP 2 RLM-FTGP 3 and RLM-FTGP 4 contain the run length values for zero, one, two, three and four.

Step 5: Extraction of Texture Features on RLM -FTGP:

Many researchers used three sets of texture features from RLM for texture classification. The first set of RLM Features (RF) is Traditional Run-Length Features. The five original features of run-length statistics derived by Galloway [27] are Short Run Emphasis (SRE), Long Run Emphasis (LRE), Gray-Level Non uniformity (GLN), Run Length Non uniformity (RLN), and Run Percentage (RP) are described by the Equation (8) to Equation (12). Chu et al. [30] proposed another set of two new features, such as Low Gray-Level Run Emphasis (LGRE), and High Gray-Level Run Emphasis (HGRE) are described in Equation (??3) to Equation (14).

In a recent study, Dasarathy and Holder [31] described another set of four feature extraction functions following the idea of joint statistical measure of gray level and run length, as follows: Short Run Low Gray-Level Emphasis (SRLGE), Short Run High Gray-Level Emphasis (SRHGE), Long Run Low Gray-Level Emphasis (LRLGE), and Long Run High Gray-Level Emphasis (LRHGE) are described in Equation (15) to Equation (18).

The novelty of the present study is it evaluated the first five RFs as described in equations from 8 to 12 for efficient classification purpose on FTGP. For a comparative analysis the present paper also evaluated all the features for classification purpose.  $?????? = 1 \text{ } ?? \text{ } ?? \text{ } ? \text{ } ??(??,??) \text{ } ?? \text{ } 2 \text{ } ?? \text{ } ?? = 1 \text{ } ?? \text{ } ?? = 1 \text{ } (8) \text{ } ????? = 1 \text{ } ?? \text{ } ?? \text{ } ? \text{ } ??(??,??) \text{ } * \text{ } ?? \text{ } 2 \text{ } ?? \text{ } ?? = 1 \text{ } ?? \text{ } ?? = 1 \text{ } ????? = 1 \text{ } ?? \text{ } ?? \text{ } ? \text{ } ??(??,??) \text{ } ?? \text{ } 2 \text{ } ?? \text{ } ?? = 1 \text{ } ?? \text{ } ?? = 1 \text{ } (10) \text{ } ????? = 1 \text{ } ?? \text{ } ?? \text{ } ? \text{ } ??(??,??) \text{ } ?? \text{ } ?? = 1 \text{ } ? \text{ } 2 \text{ } ?? \text{ } ?? = 1 \text{ } (11) \text{ } ??? = n \text{ } r \text{ } n \text{ } p \text{ } (12)$

In the above equations,  $n \text{ } r$  is the total number of runs and  $n \text{ } p$  is the number of pixels in the image.  $?????? = 1 \text{ } ?? \text{ } ?? \text{ } ? \text{ } ??(??,??) \text{ } ?? \text{ } 2 \text{ } ?? \text{ } ?? = 1 \text{ } ?? \text{ } ?? = 1 \text{ } (13) \text{ } ????? = 1 \text{ } ?? \text{ } ?? \text{ } ? \text{ } ??(??,??) \text{ } * \text{ } ?? \text{ } 2 \text{ } ?? \text{ } ?? = 1 \text{ } ?? \text{ } ?? = 1 \text{ } (14) \text{ } ????? = 1 \text{ } ?? \text{ } ?? \text{ } ? \text{ } ??(??,??) \text{ } ?? \text{ } 2 \text{ } * \text{ } ?? \text{ } 2 \text{ } ?? \text{ } ?? = 1 \text{ } ?? \text{ } ?? = 1 \text{ } (15) \text{ } ????? = 1 \text{ } ?? \text{ } ?? \text{ } ? \text{ } ??(??,??) \text{ } * \text{ } ?? \text{ } 2 \text{ } ?? \text{ } 2 \text{ } ?? \text{ } ?? = 1 \text{ } ?? \text{ } ?? = 1 \text{ } (16) \text{ } ????? = 1 \text{ } ?? \text{ } ?? \text{ } ? \text{ } ??(??,??) \text{ } * \text{ } ?? \text{ } 2 \text{ } ?? \text{ } 2 \text{ } ?? \text{ } ?? = 1 \text{ } ?? \text{ } ?? = 1 \text{ } (17) \text{ } ????? = 1 \text{ } ?? \text{ } ?? \text{ } ? \text{ } ??(??,??) \text{ } * \text{ } ?? \text{ } 2 \text{ } ?? \text{ } ?? = 1 \text{ } ?? \text{ } ?? = 1 \text{ } * \text{ } ?? \text{ } 2 \text{ } (18)$

III.

## 7 RESULTS and DISCUSSIONS

Experiments are carried out to demonstrate the effectiveness of the proposed FTGP -with RF for stone ??, Table ??I. Table 3 shows the classification rate for various group of textures by the proposed FTGP-RF with other existing methods like compound local binary pattern (CLBP) of Faisal Ahmed et.al [32] and run-length features for image classification by Yung-Kuan Chan et.al [33]. From Table 3, it is clearly evident that, the proposed FTGP-RF exhibits a high classification rate than the existing methods. The graphical representation of the percentage mean classification rate for the proposed RLM-FTGP and other existing methods are shown in Fig. 8.

## 8 Conclusion

The proposed FTGP scheme reduces the overall dimension of the image while preserving the significant attributes, primitives, and properties of the local texture. The proposed RLM-FTGP overcomes the disadvantages of the previous Run length matrices for texture classification.

LGM is an efficient tool that overcomes the traditional neighborhood problems. By directly using the entire run-length matrix for feature extraction, much of the texture information is preserved. The novelty of the proposed scheme is, it is proved that one need not necessary to evaluate all the RF on the FTGP for classification purpose. For a precise, significant and accurate classification, the present paper evaluated only 5 RLMF on FTGP, which reduced overall complexity. Comparisons of this new approach with the compound local binary pattern

(CLBP) by Faisal Ahmed et.al [32] and run-length features for image classification by Yung-Kuan Chan et.al [33] demonstrated the supremacy of the proposed FTGP method.



Figure 1: Fig. 1 :

$$LOGMO_i^0 = \text{abs}(P_i^0 - P_{i+1}^0) \quad \text{for } i = 1, 2, \dots, 9$$

Figure 2: Figure 3 :

$$FTGP_i = \begin{cases} 0 & \text{if } TNP_i < V_0 \text{ and } V_i < x \\ 1 & \text{if } TNP_i < V_0 \text{ and } V_i \geq V_x \\ 2 & \text{if } TNP_i = V_0 \\ 3 & \text{if } TNP_i > V_0 \text{ and } V_i > y \\ 4 & \text{if } TNP_i > V_0 \text{ and } V_i \leq y \end{cases} \quad \text{for } i = 1, 2, 3, 4$$

Figure 3: Fig. 4 :

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$$\text{where } V_0 = \frac{(\sum_{i=1}^4 TNP_i)}{4}$$

5

Figure 4: Fig. 5 :

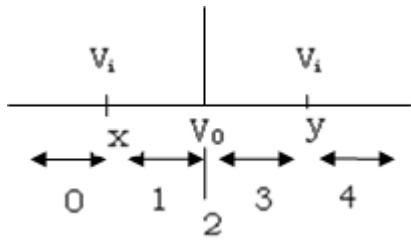
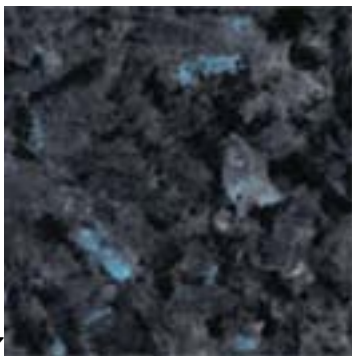
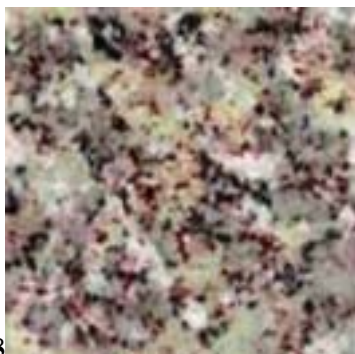


Figure 5:



617

Figure 6: Fig. 6 : 1 Fig. 7 :



8

Figure 7: Fig. 8 :

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Sno

Tex ture Name

Classifica

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Name

Classifica

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1

concrete\_bricks\_170756

94.22

Brick.0001

95.06

2

concrete\_bricks\_170757

94.58

Brick.0002

91.49

3

concrete\_bricks\_170776

89.64

Brick.0003

97.28

4

crazy\_paving\_5091370

95.2

Brick.0004

95.9

5

crazy\_paving\_5091376

96.56

Brick.0005

93.39

6

crazy\_tiles\_130356

93.54

Brick.0006

96.65

7

crazy\_tiles\_5091369

95.88

94.51

8

dirty\_floor\_tiles\_footprints\_200137

93.25

Brick.0008

93.25

9

dirty\_tiles\_200137

93.99

Brick.0009

93.37

10 floor\_tiles\_030849

96.55

Brick.0010

95.96

11 grubby\_tiles\_2565

94.68

Brick.0011

92.46

12 kitchen\_tiles\_4270064

95.48

Brick.0012

94.52

13 moroccan\_tiles\_030826

96.35

Brick.0013

93.62

14 moroccan\_tiles\_030857

95.77

Brick.0014

91.48

15 mosaic\_tiles\_8071010

96.16

Brick.0015

93.61

16 mosaic\_tiles\_leaf\_pattern\_201005060

94.97

Brick.0016

92.01

17 mosaic\_tiles\_roman\_pattern\_201005034

90.91

Brick.0017

94.58

18 motif\_tiles\_6110065

95.34

Brick.0018

92.47

19 ornate\_tiles\_030845

96.44

Brick.0019

96.13

20 repeating\_tiles\_130359

90.84

Brick.0020

95.37

[Note: Results of texture classification by proposed RF on FTGP of mosaic and brick textures in Dataset-1 © 2012 Global Journals Inc. (US) Global Journal of Computer Science and Technology Volume XII Issue XV Version I]

Figure 8: Table Ia :

**Ib**

Figure 9: Table Ib :

**2a**

Figure 10: Table 2a :

**2b**

Figure 11: Table 2b :

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**3**

| Image Dataset | with other existing methods |       |        |                          | Proposed Method<br>(FTGP-RF) |
|---------------|-----------------------------|-------|--------|--------------------------|------------------------------|
|               | Compound<br>Pattern (CLBP)  | Local | Binary | Run-length Fea-<br>tures |                              |
| Brodatz       | 90.29                       |       |        | 93.79                    | 96.31                        |
| VisTex        | 91.53                       |       |        | 93.56                    | 95.85                        |
| Mayang        | 92.34                       |       |        | 94.43                    | 97.32                        |
| Outtex,       | 91.59                       |       |        | 93.63                    | 96.96                        |
| CUReT         | 91.76                       |       |        | 93.46                    | 97.54                        |
| Paulbourke    | 90.98                       |       |        | 94.56                    | 96.77                        |
| Average       | 91.41                       |       |        | 93.91                    | 96.79                        |

Figure 12: Table 3 :



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[Lee et al.] , W.-L Lee , - C Yung , Chen , - C Ying , K.-S Chen .

[Feng et al. ()] ‘A Coarse-to-Fine Classification Scheme for Facial Expression Recognition’. X Feng , A Hadid , M Pietikainen . *ICIAAR 2004 Proceedings*, Lecture Notes in Computer Science 3212 II 2004. p. . (Image Analysis and Recognition)

[Ojala et al. ()] ‘A comparative study of texture measures with classification based on feature distribution’. T Ojala , M Pietikäinen , D Harwood . *Pattern Recognition* 1996. 29 p. .

[Hadid et al. ()] ‘A Discriminative Feature Space for Detecting and Recognizing Faces’. A Hadid , M Pietikainen , T Ahonen . *IEEE Conference on Computer Vision and Pattern Recognition II*, 2004. p. .

[Jiji and Ganesan ()] ‘A new approach for unsupervised segmentation’. Wiselin Jiji , G Ganesan , L . *Applied Soft Computing* 2010. 10 p. .

[Vijaya Kumar et al. ()] ‘A New Method of Texture Classification using various Wavelet Transforms based on Primitive Patterns’. V Vijaya Kumar , U S N Raju , K Chandra Sekaran , V V Krishna . *Vision and Image Processing*, 2008. 8 p. . (GVIP)

[Reed and Buf ()] ‘A review of recent texture segmentation and feature extraction techniques’. T R Reed , J M H Buf . *CVGIP: Image Understanding* 1993. 57 p. .

[Mohan et al. ()] *Adulthood classification based on geometrical facial features*, Chandra Mohan , V Vijayakumar , A Damodaram . 2009. (ICGST)

[Mohan et al. ()] ‘Classification of child and adult based on geometric features of face using linear wavelets’. Chandra Mohan , M Vijaya Kumar , V Sujatha , B . *IJSIP* 2010. 1 (3) p. .

[Jiji and Ganesan ()] ‘Comparative analysis of colour models for colour textures based on feature extraction’. Wiselin Jiji , G Ganesan , L . *Int. Jour. of Soft computing* 2007. 2 (3) p. .

[Ahmed et al.] *Compound Local Binary Pattern (CLBP) for Facial Expression Recognition*, Faisal Ahmed , A S M Bari , Emam Hossain . p. 2011.

[Kumar et al. (2009)] ‘Employing Long Linear Patterns for Texture Classification relying on Wavelets’. Vijaya Kumar , .V , U S N Raju , Chandra Sekaran , V V Krishna . *ICGST-GVIP Journal* 1687-398X. January 2009. (8) p. .

[Ahonen et al. ()] ‘Face description with local binary patterns: application to face recognition’. T Ahonen , A Hadid , M Pietikäinen . *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2006. 28 (12) p. .

[Ahonen et al. ()] ‘Face Recognition Based on the Appearance of Local Regions’. T Ahonen , M Pietikainen , A Hadid , T Maenpaa . *17th International Conference on Pattern Recognition III*, 2004. p. .

[Ahonen et al. ()] ‘Face Recognition with Local Binary Patterns’. T Ahonen , A Hadid , M Pietikainen . *Computer Vision, ECCV Proceedings*, 2004. p. .

[Feng et al. ()] ‘Facial Expression Recognition with Local Binary Patterns and Linear Programming’. X Feng , M Pietikainen , A Hadid . *Pattern Recognition and Image Analysis* 2005. 15 p. .

[Dash and Liu ()] *Feature Selection for Classification. Intelligent Data Analysis*, M Dash , H Liu . 1997. Elsevier. p. .

[Belur et al. (1981)] ‘Image characterizations based on joint gray level-run length distributions’. V Belur , Edwin B Dasarathy , Holder . *Pattern Recognition Letters* 1981. August 1991. 12 p. .

[Chan and Chang ()] ‘Image matching using run-length feature’. Yung-Kaun Chan , Chin-Chen Chang . *Pattern Recognition Letters* 2001. 22 p. .

[Zhang et al. ()] ‘Learning optimal filter representation for texture classification’. P Zhang , J Peng , B Buckles . *International Conference on Pattern Recognition*, (Hong Kong) 2006. 2 p. .

[Ojala et al. ()] ‘Multiresolution gray-scale and rotation invariant texture classification with local binary patterns’. T Ojala , M Pietikäinen , T Mäenpää . *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2002. 24 (7) p. .

[Lucieer et al. ()] ‘Multivariate texturebased segmentation of remotely sensed imagery for extraction of objects and their uncertainty’. A Lucieer , A Stein , P Fisher . *International Journal of Remote Sensing* 2005. 26 (14) p. .

[Mohan et al. ()] ‘Novel method of adult age classification using linear wavelet transforms’. Chandra Mohan , V Vijayakumar , V Venkata Krishna . *IJCSNS*, 2010. p. .

- [Jafari-Khouzani and Soltanian-Zadeh ()] ‘Radon transform orientation estimation for rotation invariant texture analysis’. K Jafari-Khouzani , H Soltanian-Zadeh . *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2005. 27 (6) p. .
- [Pietikäinen et al. ()] ‘Rotation-invariant texture classification using feature distribution’. M Pietikäinen , T Ojala , Z Xu . *Pattern Recognition* 2000. 33 p. .
- [Paclik et al. ()] ‘Supervised segmentation of textures in backscatter images’. P Paclik , R Duin , G Van Kempen , R Kohlus . *Proceedings of the 16th International Conference on Pattern Recognition*, (the 16th International Conference on Pattern RecognitionQuebec City) 2002. p. .
- [Van Gool et al. ()] ‘Survey-texture analysis an no 1983’. L Van Gool , P Dewaele , A Oosterlinck . *Computer Vision, Graphics Image Processing*, 1985. 29 p. .
- [Galloway (1975)] ‘Texture analysis using gray level run lengths’. M M Galloway . *Comput. Graphics Image Process* June 1975. 4 p. .
- [Samal et al. ()] ‘Texture as the basis for individual tree identification’. A Samal , J R Brandle , D S Zhang . *Information Sciences* 2006. 176 p. .
- [Raju et al. ()] ‘Texture Classification Based On Extraction Of Skeleton Primitives Using Wavelets’. U S N Raju , Eswar Reddy , Vijaya Kumar , B Sujatha . *Information Technology Journal* 2008. (7) p. .
- [Reddy et al. (2007)] ‘Texture Classification by Simple Patterns on Edge Direction Movements’. Eswara Reddy , B , A Rao , A Suresh , V Vijaya , Kumar . *IJCSNS International Journal of Computer Science and Network Security* November 2007. 7 (11) p. .
- [Raju et al. ()] ‘Texture Description using Different Wavelet Transforms Based on Statistical Parameters’. U S N Raju , V Vijaya Kumar , A Suresh , M Radhika Mani . *proceedings of the 2nd WSEAS International Symposium on WAVELETS THEORY & APPLICATIONS in Applied Mathematics, Signal Processing & Modern Science (WAV ’08)*, (the 2nd WSEAS International Symposium on WAVELETS THEORY & APPLICATIONS in Applied Mathematics, Signal Processing & Modern Science (WAV ’08)Istanbul, Turkey) 2008. p. .
- [Marzabal et al. ()] ‘Textured-based characterization of defects in automobile engine valves’. A Marzabal , C Torrens , A Grau . *Proceedings of the Ninth Symposium on Pattern Recognition and Image Processing*, (the Ninth Symposium on Pattern Recognition and Image Processing) 2001. p. .
- [Tuceryan and Jain ()] ‘The Handbook of Pattern Recognition and Computer Vision’. M Tuceryan , A K Jain . *Texture analysis*, C H Chen, L F Pau, P S P Wang (ed.) (Singapore) 1998. World Scientific. p. . (second ed.)
- [Koller and Sahami ()] ‘Toward optimal feature selection’. D Koller , M Sahami . *Proceedings of the 13th International Conference on Machine Learning*, (the 13th International Conference on Machine LearningBari, Italy) 1996. p. .
- [Hsieh ()] ‘Unsupervised segmentation of ultrasonic liver images by multiresolution fractal feature vector’. Hsieh . *Information Sciences* 2005. 175 p. .
- [Chu et al. ()] ‘Use of gray value distribution of run lengths for texture analysis’. A Chu , C M A Sehgal , J F Greenleaf . *Pattern Recognition Letters* 1990. 11 (6) p. .