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ROTATIONAL INVARIANT FUZZY ROUGHNESS FEATURE FOR TEXTURE CLASSIFICATION

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ABSTRACT

The need of texture classification arises in several disciplines such as industry, medical, satellite imaging computer vision and image analysis. The success of classification process depends on the selection of feature set. We propose a rotational invariant fuzzy based texture feature for image classification. This work employs a fuzzy membership value to the roughness feature extracted using the Fractional Brownian Motion (FBM) model. The discriminative capability of the proposed approach is tested for image classification. For classification, KNN algorithm is used Brodatz texture database is used for evaluating the proposed approach. This work proves that roughness feature tolerates the rotational variance problem. The fuzzy based approach provides the solution for imprecision and improves the classification accuracy.

KEYWORDS: Fuzzy Texture Feature, Texture Classification, Texture Roughness

INTRODUCTION

Texture analysis is an active research topic in the field of pattern recognition. Texture plays an important role in segmenting an image, texture synthesis for graphic application and classification of images. Texture classification is widely used because it has a wide range of applications such as remote sensing, medical image analysis and fabrics inspection. The success rate of classification or segmentation requires an efficient description of image texture. The textural features prove its significance in image analysis based on local difference in intensity or colour

Based on the local difference, several texture descriptors have been proposed for image description. Among them, local binary pattern (LBP) based method become very popular for its improved performance. In LBP based methods, calculation is done simply by comparing a pixel with its neighbours. Most of the LBP based descriptors have gained popularity for its computational simplicity. But LBP and its variants fail to generate the same code for the same type of texture structures.

A major problem in texture analysis is that textures in real world are not uniform due to orientation changes and scale changes. Scale and rotation invariance is the main issue to be addressed in texture classification. The objective of this work is to propose a rotational invariant fuzzy based texture feature for image classification.

Motivation and Justification for the Proposed Work

Texture analysis approaches can be classified into four categories: (i) Structural (ii) Statistical (iii) Model based and (iv) Transforms methods the structural approaches represent the texture by well defined primitives and their spatial placement rules. Statistical methods focus on statistical properties of the texture. Statistical methods analyze the distribution of gray values and compute local feature for each pixel in the image. Co-occurrence matrix and gray scale differences are the widely used statistical methods for texture analysis. Local Binary pattern texture descriptor was proposed by Ojala et al [21]. This descriptor incorporates both statistical and structural approaches for texture analysis. Model based approaches use fractal and stochastic models. In model based approach, a set of parameters from the variation of pixel elements are estimated and used to define the image. Transform methods use Fourier spectrum, Gabor filters, wavelet transform and other transform techniques.

Coarseness, contrast, directionality, likeliness, regularity and roughness are the set of visual features used by Tamura et al [20]. Since the roughness feature is insensitive to illumination, contrast variation, the roughness feature was considered by different researchers. Several methods have been used to characterize texture by its roughness using fractal dimension. The Fractal model has been used by many researchers for texture analysis. Fractal was first introduced by Mandelbrot [12]. He used this concept for measuring surface roughness.

In [9], the authors used fractal functions for natural scene image analysis. Fractal dimension shows a strong correlation with visual perception of surface roughness. The reason for selecting fractal dimension feature is fractal dimension is insensitive to image scaling [15] and rotational invariant. Liang Chen et al [7] applied the concept of the normalized fractional Brownian motion model for liver image to find liver boundary. Fractional Brownian motion model (FBM) was proposed by Lundahl et al [11]. Normalized Fractional Brownian motion model (NFB) was used by [3] and [22] to classify ultrasonic liver images. Dimitrios Charalampidis et al [6] proposed directional roughness feature and weighted roughness features for image classification. Arrault et al [1] used wavelet concept for computing roughness value. In [8] the authors proposed a wavelet rational invariant roughness feature set for classification and segmentation based on an extension of fractal dimension features. Manik Varma et al [13] derived local fractal features for classifying texture images of different viewpoint and illumination conditions.

In [24], Zhang Jian et al proposed an approach to extract the average texture cycle to describe the surface roughness. Sebastien Deguy et al [18] presented a new method using the multiscale fractional brownian motion texture model and a new parameter called intermittency which describes a degree of presence of the textural information. In [16], the authors proposed a new image characteristic namely gradient factor of the image and this was used to estimate the roughness parameters. Marcelo L Alves et al [14] used Haralick descriptors to describe the surface texture and performed classification. Yong Xia et al [23] proposed a multifractal estimation algorithm and a set of multifractal descriptors to characterize the local scaling properties of textures. The fractal Brownian motion is used to estimate the fractal dimension of ultrasound images of breast lesion [5] and the authors classified the breast lesion into benign and malignant based on fractal analysis.

Fuzzy binary pattern was proposed by Keramidas et al [10] and proved its robustness against noise. Chrianjeevi *et al* [4] applied a fuzzy membership transformation to co-occurrence vector for detecting moving objects. A fuzzy rule based system was used by Rocio A. Lizarraga-Morales [17] for texture classification. Fuzzy Local Texture Pattern [FLTP] was proposed by E. M. Srinivasan *et al* [19] and prove its robust performance.

From the literature it is clear that fractal concept was used for characterizing texture region by many researchers. Incorporating a Fuzzy logic will improve the performance. To the best of the knowledge of the authors, the role of fuzzy in mapping feature vector into its subclasses has not been analyzed so far. Hence an attempt has been made in this work to analyze the impact of fuzzyfying roughness feature vector derived using FBM.

Outline of the Proposed Approach

The proposed system diagram is shown in the Figure 1. The proposed method consists of two phases: (i) Training Phase (ii) Testing Phase. In training phase the roughness feature is extracted and the feature is fed into fuzzy system to get a fuzzy feature vector. The fuzzy feature vector contains 3 values. They are membership to rough, membership to medium rough and membership to smooth. The fuzzy feature vector value of each image contains discriminative information about the image. In testing phase, the same procedure is followed and fuzzy feature vector is generated. For fuzzy feature vector based classification, a nonparametric k-nearest neighbor (KNN) classifier and Euclidean distance measure is used.

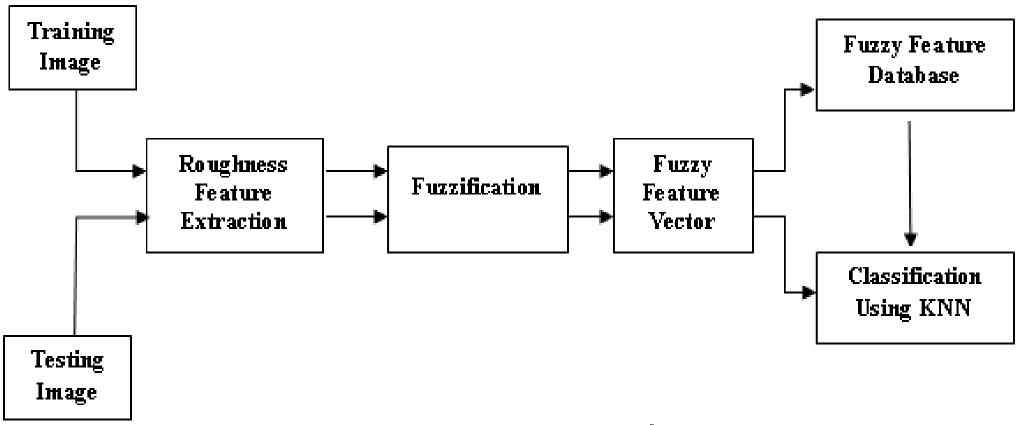


Figure 1: Classification Procedure for the Proposed Approach

METHODOLOGY

Feature Extraction

Features play a significant role in image classification. The transformation of an image into its set of features is called feature extraction. Useful features of the image are extracted from the image for classification purpose. It is a challenging task to extract good feature set for classification. Research work is going on for deriving feature set for image analysis. In this paper, we consider the roughness feature. We classify the roughness class into three subclasses based on the amount of property present in the region. They are Rough, Medium Rough, and Smooth.

Roughness

Roughness is one of the surface properties which is defined as small irregularities present on a surface. The irregularities characterize the texture of the surface. Roughness is only a result of abrupt transition located at object edges. The fractal concept was introduced by Mandelbrot for measuring surface roughness. It was later applied by Pentland for natural scene analysis. Kuler used this feature for image segmentation.

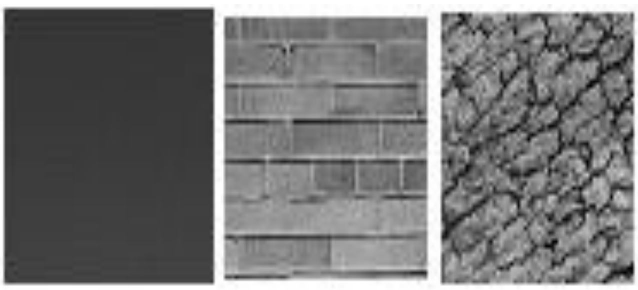


Figure 2: Sample Images for Smooth, Medium Rough and Rough Surfaces

Different fractal method has been proposed. Fractional Brownian Model (FBM) is one of the fractal methods described by Mandelbrot. This FBM has been used for roughness feature extraction in this work. For a given NxN image I, the intensity difference Id_i is defined by the following formula.

$$Id(k) = [\sum_{x=0}^{N-1}\sum_{y=0}^{N-k-1}\frac{|\,I(x,y) - I(x,y+k)\,|}{N(N-k)} + \sum_{y=0}^{N-1}\sum_{x=0}^{N-k-1}\frac{|\,I(x,y) - I(x+k,y)\,|}{N(N-k)} + \sum_{x=0}^{N-k-1}\sum_{x=0}^{N-k-1}\frac{|I(x,y) - I(x+k,y+k)|}{(N-k)^2} + \sum_{x=0}^{N-k-1}\sum_{y=0}^{N-k-1}\frac{|I(x,N-y) - I(x+k,N-(y+k))|}{(N-k)^2}]/4$$

I(x,y) is the intensity value of the pixel and k is the distance.

Fuzzification of Roughness Feature

As roughness feature is a vague textural property, fuzzy logic is employed in this work for representing the imprecision. In most of the fuzzy based approaches, fuzzy logic has been introduced for deriving the descriptor and in classification phase. In this work, we introduce the fuzzy logic for mapping the feature vector into corresponding feature subclasses. The fuzzy logic used in this work operates on the concept of membership. Based on the degree of membership, the feature vector values are mapped. We derived a mathematically simple Trapezoidal-shaped membership functions. Membership functions are chosen based on the result of the feature values. The Graphical representation of the membership function for roughness feature is demonstrated in the figure 2.

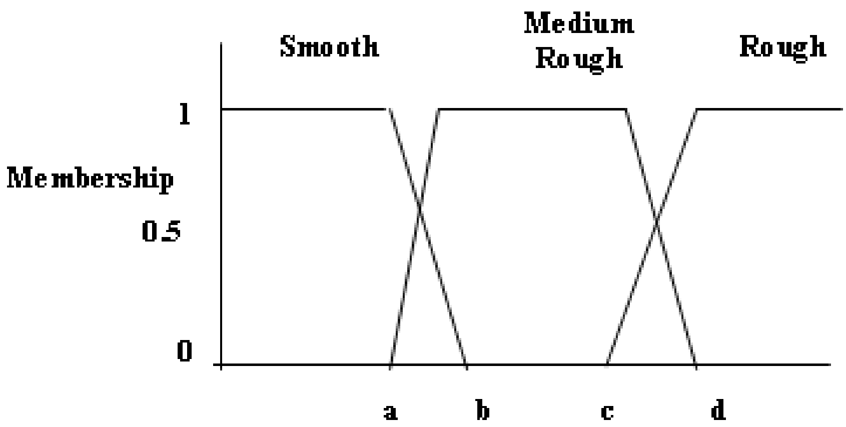


Figure 2: Fuzzy Membership Function for the Roughness Features

The trapezoidal curve is a function of a vector which depends on four scalar parameters a, b, c, and d. The membership function is defined for as follows

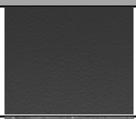
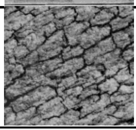
$$\mu\text{Smooth}(\text{Xi}) = \begin{cases} 1\ if\ Xi \le a \\ \frac{(b-Xi)}{(b-a)}\ if\ a < Xi < b \\ 0\ otherwise \end{cases}$$

$$\mu\text{Medium\_Rough}(Xi) = \begin{cases} 0 \; if \; Xi \leq a \\ \frac{(Xi-a)}{(b-a)} \; if \; a < Xi < b \\ \frac{(d-Xi)}{(d-c)} \; if \; c \leq Xi \leq d \\ 1 \; if \; b \leq Xi \leq c \\ 0 \; if \; Xi \geq d \end{cases}$$

$$\mu\text{Rough}(Xi) = \begin{cases} 1 \; if \; Xi \geq d \\ \frac{(Xi-c)}{(d-c)} \; if \; c < Xi < d \\ 0 \; otherwise \end{cases}$$

Based on the above considerations, the membership values are calculated. The following table contains the three different sample images and membership value for each class of roughness region.

Table 1: Sample Images with Membership Value for Each Class (Smooth, Medium Rough and Rough)

Image	Membership Value for Smooth	Membership Value for Medium Rough	Membership Value for Rough
	1	0	0
	0	0.4448	0.5552
	0	0.0852	0. 9148

CLASSIFICATION

In this work, a nonparametric K-nearest neighbour classifier is used for roughness feature based classification. **The** KNN algorithm is a method for classifying images based on closest training samples in the feature space. The algorithm for k-Nearest Neighbor classification is as follows.

- Divide the data into training samples and testing samples. In this work, training samples are extracted from images with 0^0 rotation and testing samples are extracted from images with 30^0,60^0, 90^0,120^0,150^0 and 180^0 rotation.
- For each test sample, the K nearest training samples are found by calculating the distance between training samples and testing samples using Euclidean distance measure.

  The Euclidean distance measure is defined as

$$D_e(S,M) = \sum_{i=1}^{n} \sqrt{S_i^{\,2} - M_i^{\,2}}$$

S and M are the sample image feature to be tested and training image feature of the training set, n indicates the total number of bins. In our experiment, n value ranges from 1 to 3 represents the roughness value distribution from smooth to rough. The value of the computed distance value indicates the probability that two sample distributions come from the same class. The lower the value, the higher the probability that the two samples are from the same class.

EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

Experiment 1

In the first experiment, we proved the ability of roughness feature for classification and its rotational invariance property. We considered 16 classes of images from Brodatz database. In training phase, 100x100 size sample regions are extracted from Bark, Brick, Bubbles, Grass, Wood, Straw, D73, D109, D93, D82, D77, D104, D24, D49, D105 and D106 with 0^0 rotation. Roughness feature values are calculated and kept in a feature database. In testing phase, samples are taken from same set of images with rotation angles 30^0, 60^0, 90^0, 120^0, 150^0 and 180^0. For calculating membership value, we set the values as A=9, B=14, C=17, D=21. If the test sample is assigned to the corresponding class, then the classification is considered as correct. Otherwise, it is a misclassification. Performance of the proposed approach is measured by the classification rate. The classification rate is the total number of classified image divided by the total number of images in the testing set. The classification accuracy for this experiment is tabulated in Table 2.

Table 2: Classification Accuracy for Different Orientation

No. Of Samples	30^o	60^o	90^o	120^o	150^o	200^o	Overall Accuracy
N=1	69.23	61.54	53.85	61.54	76.92	69.23	65.39
N=2	78.35	70.66	62.97	70.66	86.04	78.35	74.51
N=4	85.56	79.88	72.55	80.56	92.66	88.53	83.29

From Table 2 it is observed that the overall accuracy is increasing as K value increases. The roughness feature also posses the rotational invariance property.

Experiment 2

The second experiment was conducted to analyse the performance of proposed fuzzy based roughness feature. Images which are having overlapping roughness values are considered. For training, samples are taken from Bark, Brick, Bubbles, Grass, Leather, Pigskin, Raffia, Sand, Straw, Water, Weave, Wood and Wool images with 0 degree rotation. For testing, sample regions are taken from the same set of images with various view point. The various viewpoints 30^0, 60^0, 90^0,120^0, 150^0 and 200^0 are considered for testing. We used the same values for A, B, C and D as set in Experiment 1. The fuzzy based approach helps the roughness feature to improve the classification accuracy. The results for the proposed approach is tabulated in Table 3.

Table 3: Classification Accuracy for the Proposed Approach

No. of Samples	30^o	60^o	90^o	120^o	150^o	200^o	Overall Accuracy
K=1	92.31	92.31	84.62	76.92	100	92.31	89.75
K=2	95.64	94.32	87.55	82.65	98.15	93.65	91.99
K=4	97.78	95.56	89.87	84.65	99.51	95.96	93.88

In the first approach, roughness feature values are directly used whereas in the second approach the roughness feature values are converted into fuzzy membership values and this values are used for classification. As there are some overlapping values of roughness feature in the image set, the non-fuzzy method gives 83.29% of classification accuracy as a maximum accuracy. The fuzzy based approach overcomes the drawback of previous method. The fuzzy based method improves the classification accuracy by 10%. It is proved that the fuzzy based approach tolerates the imprecision and uncertainty.

CONCLUSIONS AND FUTURE SCOPE

In this paper, a fuzzy based approach is presented for texture image classification. The roughness textural feature is transformed into fuzzy feature vector by using fuzzy membership function. The performance of the proposed approach is tested on images from Brodatz database. For testing, KNN algorithm along with Euclidean distance measure is used. The proposed method is reliable for texture characterization. We achieved 89.75% classification accuracy. Experimental results show that the proposed approach provides an efficient method for representing texture information with high discriminative ability and robust against viewpoint orientations. Further research is going for applying this method for medical image classification.

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