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Fuzzy Based Scaling Rotational and Transformation for Invariant Texture Classification

Palanivel N and Gokulavani S

Assistant Professor, PG Scholar
npalani76@gmail.com,gokulavanicse@gmail.com

Abstract

Texture classification is important step in image processing and computer vision applications. The proposed method offers efficient way to classify the invariant texture using discrete shearlet transform and fuzzy logic. The texture features of an image are represented using shearlet energy features and shearlet co-occurrence features. These features are obtained from block based energy form of shearlet decomposed image using two levels of discrete shearlet transform with two directions and by varying the block size. Finally, the obtained parameters are used to classify the texture in an image using fuzzy logic classifier.

Keywords: *Scaling, Rotation, Transformation, Invariant Texture, Classification, Discrete Shearlet, Fuzzy*

1. International

Texture is one of the basic properties in important for many applications which include image segmentation and classification which is purely based on three-dimensional arrangement of intensity and color. Texture segmentation is additionalsignificant topic in image processing. Itsgoal is to segmenting a textured image into several regions without a priori significant about the textures. An effective and efficient texture segmentation method will be very useful in applications like the analysis of mid-air images, biomedical images and seismic images as well as the automation of industrial inspections.The classification can be done by two ways one is supervised classification and the other is unsupervised classification .The classification process involves into two phases. One is learning phase the other is recognition phase. As segmentation is the significant step in image processing, it helps to classify the image in order to reach the scrupulous location. Generally texture analysis methods are divided into structural method, statistical method and model based method. These existed models offers maximum effective tools for analysing invariant texture. These models have less comparative properties while comparing with other to classify image. By using this reasonable feature we can easily classify image by applying it. Though various approach are accessible. The main advantages are when scaling the image, its features never changes from its position. Likewise, it is similar for rotation and transformation of invariant textures. Therefore, most of the surviving approaches for the image classification are attainable but, by applying the proposed method the performance gets increased.

2. Related Work

2.1. Scaling Invariant Texture Classification Using Fuzzy

Scaling is the process to resize from its original image. Scaling is a process that involves an adjustment between efficiency, softness and keenness. When the image size is reduced or enlarged the pixel from the image become increasingly visible. Scaling could also be done by applying some methods and algorithms such as cubic interpolation

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technique, bilinear transformation technique and super sampling method. Even though resizing may happen the image feature do not change this can be applicable for any types of image from multiple database. Fuzzy classifier is the non-linear mapping function of an input feature of vector element into a scalar output. The fuzzy classifier is developed with the Gaussian membership function. Now the classifier is ready to categorize the image based on fuzzy logic in this work, scaling invariant texture classification using fuzzy logic approach, two features are obtained from the image sub-band analysis of discrete wavelet transform co-efficient up to fifth level of decomposition and eight features are extracted from gray level co-occurrence matrix. The parameters from the extracted features are updated for further procedure in order to calculate the discrete wavelet coefficients. Then it works by succeeding its approaches.

2.2. Rotational Invariant Fuzzy Roughness Feature for Texture Classification

Rotation is a circular movement of an object around a centre of rotation. When rotating the image its angle may change but their features never change in this work, therefore, coarseness found in the images are extracted and identified using Fractional Brownian motion model. Second step is for Fuzzification. By denoting the coarseness feature is an indefinite textural property, it can be properly analysed. The vector contains three values. They are membership to rough, membership to medium rough and membership to smooth. Classification employs with the fuzzy membership value. Based on the degree of membership, the vector rate of each pixel contains discriminative information about the image. The generated fuzzy feature values are been stored in the database. Finally, the various database images of training samples and the input image of testing samples are applied and get classified image using KNN-Algorithm.

2.3. Wavelet Transform in Image Region

In this wavelet transform in image region work, it uses discrete wavelet transform and discreteFourier transform. Discrete wavelet transform for wavelet decomposition of image. Discrete Fourier transform for analysing the signal strength. Both are combined to offer multi resolution between time scale analyses. In this paper, the boundaries are analysed the values are been calculated. Class boundaries are represented by matrix values. The image is divided into various segments. For each segments mean and variance are processed.

The leading level decomposition of discrete wavelet transform is formulated. Next step of second level decomposition of discrete wavelet transform are computed. The segmented pixel value and position of each feature are calculated. The obtained results are similar for both the levels of decompositions but there is a slight variance estimated by the discrete wavelet transform. The comparative performance of discrete wavelet is less than obtained analysis of discrete Fourier transform.

3. Overview the System

The steps for the overall process:

3.1. Extracting Sub-band of an Image

The texture images are subjected into two levels of discrete shearlet transform with two directions in order to extract sub-bands of the image. The obtained sub-bands of the image can be divided into M*N blocks of original image. For the each blocks of the image the energy is computed through the mentioned equation.

$$E_b = \frac{1}{M * N}\sum_{i=1}^{M} + \sum_{j=1}^{N} |S_e(i, j)|$$

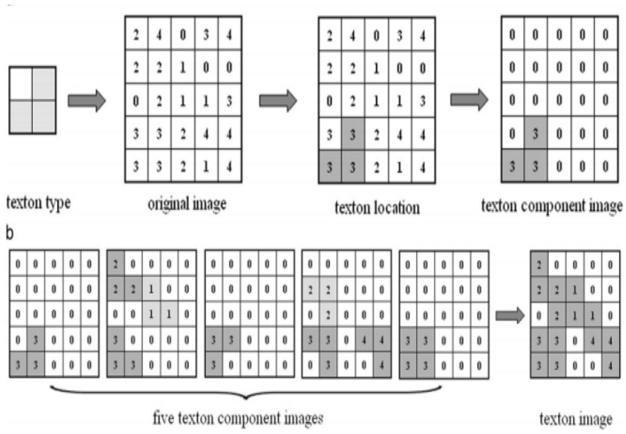

Figure 3.1. Texton Representation

Where, M represents the number of rows and N represents number of columns are incorporated to divide the each parts of the image into blocks$S_e(i, j)$. It defines integral sum of energy pixel value of the sub-band S.

3.2. Texton Co-Occurrence Matrix

After the energy computed through sub-band analysis it has been taken for texton representation. For the gray level image feature extraction texton co-occurrence Matrix is used here. The purpose of TCM is to differentiate the image features of each pixel based on the interrelation to the textons representation. Let g be the unit vector corresponding to it. G of the gray level in the image, then the following vector co-ordinate with the function f(X, Y)

$$U = \frac{\partial G}{\partial x} g$$

$$V = \frac{\partial G}{\partial y} g$$

$$g_{xx} = u^T v = \left|\frac{\partial G}{\partial x}\right|^2$$

$$g_{yy} = v^T v = \left|\frac{\partial G}{\partial y}\right|^2$$

$$g_{xy} = u^T v$$

$$u^T v = \frac{\partial G}{\partial x} \cdot \frac{\partial G}{\partial y}$$

The texton templates can be represented into five unique frames to identify the textons. The texton templates are mapped to five unique combinations of texton component images. Finally, the component images are combined together into texton identified image by enumerating boundary of all mapped regions. The adjacent pixels are represented by P1=(X1, Y1), P2=(X2, Y2). Weight of the pixels are denoted as T (P1) =W1, T (P2) =W2. The orientation angle of the image is indicated as θ (P1) = v1 and θ (P2) = v2.

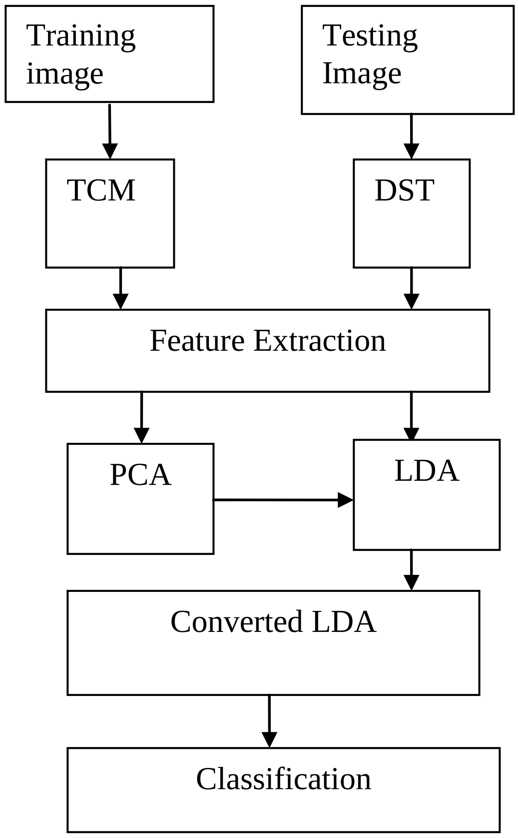

Figure 3. 2. Block Diagram for Texture Classification

3.3. Discrete Shearlet Transform

Feature extraction is one of the most important steps. For the discrete shearlet transform a new discrete band signature is planned. The group of N*N database image are derived from the texton sub space image. That image can be used to perform on discrete shearlet transform.

$$(x, y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} x(u, v)\overline{y(u, v)}$$

$$\hat{f}[k_1, k_2] = \frac{1}{N} \sum_{n1,n2=0}^{N-1} f[n_1, n_2] \ldots.$$

$$\ldots.. e^{-2\Pi i(\frac{n_1}{N}k_1 + \frac{n_1}{N}k_2)}$$

$$\hat{f}(\xi_1, \xi_2)\overline{V(2^{-2j}\xi_1, 2^{-2j}\xi_2)}$$

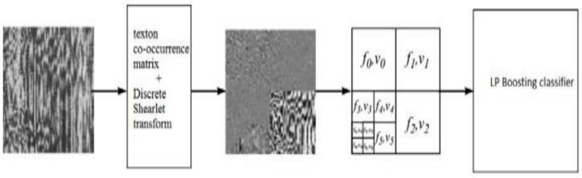

Figure3. 3. Block Diagram for Discrete Shearlet Transform

Now the discrete shearlet transform is now ready to enhance the image for texture classification.

3.4. Transforming Image into Principle Component Analysis

The extraction of sub-band image is utilized for principal component analysis. The PCA can be achieved through calculating the algorithmic means of all the feature information vectors F1, F2, F3, and FN containing the curve let coefficients through

$$\mathrm{x} = \frac{1}{n}\sum_{j=1}^{n} F_j$$

Principal component analysis is statistical analysis. It is concerned with elucidating the covariance structure of set of variables. It allows identifying the principal directions in which the data varies. If the variation of the data is occurred by other relationship, Finally, PCA issues a way of dropping the dimensionality of the data set. As for the computational terms in the principal components are found by calculating the Eigen vectors and Eigen values of the data covariance matrix. The variation of each feature information vector and mean is computed through **σj = Fj-x.** The obtained result is transformed to Linear Discriminant Analysis.

3.5. Linear Discriminant Analysis

When the transformation of the principle component analysis is carried out that image is transformed to linear Discriminant analysis. Mean is calculated from all the feature information F1, F2, F3, FN containing curve let coefficient. The covariance matrix is computed to find the positions of the elements. $\mathrm{Y} = \mathrm{W}^{Z}$ Where W is the Eigen vector of${F_w}^{-1}$

$$F_w = \sum_{j=1}^{c} \sum_{i=1}^{M} (x_{ij} - \mu_j)(x_{ij} - \mu_j)^{\tau}$$

$$F_b = \sum_{j=1}^{c} M_i(\mu_j - \mu)(\mu_j - \mu)^{\tau}$$

The Eigen vector and Eigen values are correlated through covariance matrix. Here M is the number of illustration. C defines the number of data set

3.6 Fuzzy Logic Classification

Fuzzy logic method of classification converts vector of input values into scalar values. This can be obtained through fuzzy membership function through

$$\mu_m(f) = e^{-0.5\left(\frac{-m}{\sigma}\right)^2}$$

M is the mean value of vector coefficients. $\sigma$is the standard deviation of coefficients of vector elements into fuzzy logic classifier. The distinguished role of the fuzzy logic classifier is to separate some set of computed threshold value. When the results of every procedure are processed it has been thrown into its range either 0 or 1. Based on the ranges of value, fuzzy classification is done. Next step is to find the distance between both the images of testing and training images. Finally, the texture is classified

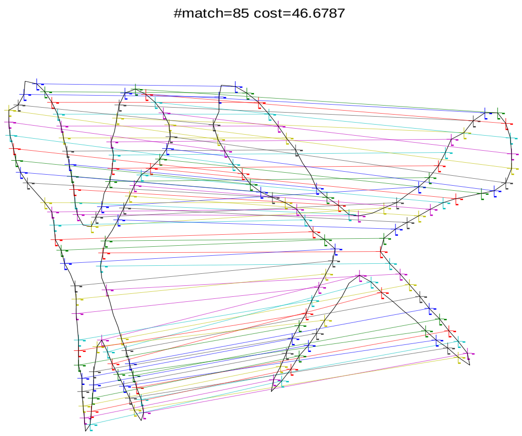

Figure 6.1. Texture Classification

4. Result Analysis

This method was tested on several images from the database. The proposed system was now able to perform the classification of invariant texture. And it is implemented with the help of MATLAB tool and tool and run on desktop PC with a 3.09GHz Intel and 1.09 RAM. We have implemented the image classification then we evaluated the parameters for the input image using features.

5. Conclusion and Future Work

This paper illustrates the suitability of using this model to classify the invariant texture in an image for computer vision based application. Fuzzy logic is an outstanding tool to overcome the suspicions involved in the indefinite information. In the proposed work of fuzzy based scaling, rotation and transformation for invariant texture classification represented by defining the shearlet co-occurrence features and shearlet energy features which attains the superior results for classifying the image texture by increasing the accuracy of 0.16% higher than the existed results.

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Authors

N. Palanivel, presently working as Associate Professor in Department of Computer Science and Engineering in Manakula Vinayagar Institute of Engineering and Technology (affiliated to Pondicherry University, Puducherry).

Gokulavani. S, completed Bachelor of degree in Computer Science and Engineering at 2012 and Pursuing Master degree in Computer Science and Engineering under Pondicherry University, MIT (Manakula Vinayagar Institute of Technology)