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Texture Classification Approach Based On Combination of Random Threshold Vector Technique and Co-Occurrence Matrixes

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Abstract:

Texture classification became one of the problems which has been paid much attention on by image processing scientists since late 80s. Consequently, since now many different methods have been proposed to solve this problem. In most of these methods the researchers attempted to describe feature's set which provide good dimensionality and severability between textures. In RTV method, a new feature's set derived from the fractal geometry is called the random threshold vector (RTV) for texture analysis. The results have shown, this method can't provide high accuracy rate in texture classification. So in this paper an approach is proposed based on combination of RTV and Co-occurrence matrixes. First of all, by using a unique threshold method the first dimension of feature vector is calculated. After that, by using RTV method, the entropy is computed of Co-Occurrence matrixes. So, the vectors have two dimensions, one of them is threshold dimension and another is the entropy's value for the co-occurrence matrix. In the result part, the proposed approach is applied on some various datasets such as Brodatz and Outex and texture classification is done. High accuracy rate shows the quality of proposed approach to classification textures. In addition the random threshold vector technique based on co-occurrence matrix contains great discriminatory information which is needed for a successful analyzed. This approach can use in various related cases such as texture segmentation and defect detection.

Keywords: Random Threshold Vector, Texture classification, Feature extraction, Fractal geometry, Entropy estimation

Introduction:

We know that a lot of variations exist in the natural texture features that should be opted according to the characteristic of texture image to get the best practical applications for texture classification. Different object's images are best characterized by texture classification methods. Also texture classification methods arrived success in their operation that are used in industrial applications, bio medical, remote sensing areas and target recognition. In the last decade numbers of significant methods were proposed that could express texture properties of the image.

Rian and zhian[1] categorized the techniques used to texture analysis or classification in four categories, statistical approaches, Structural approaches filter based methods, and model based approaches. Table 1 shows a summary list of some of the key texture analysis methods that have been applied to Texture classification or segmentation. Clearly, statistical and filter based approaches have been very popular. Statistical texture analysis methods [2, 3] measure the spatial distribution of pixel values. They are well rooted in the computer vision world and have been extensively applied to various tasks. A large number of statistical texture features have been proposed, ranging from first order statistics to higher order statistics. Amongst many, histogram statistics, co-occurrence matrices, autocorrelation, and local binary patterns have been applied to texture Analysis or Classification. In structural approaches [4, 5], texture is characterized by *texture primitives* or texture elements, and the spatial arrangement of these primitives. Thus, the primary goals of structural approaches are firstly to extract texture primitives, and secondly to model or generalize the spatial placement rules. The texture primitive can be as simple as individual pixels, a region with uniform gray levels, or line segments. The placement rules can be obtained through modeling geometric relationships between primitives or learning statistical properties from texture primitives. The filter based techniques [6, 7] largely share a common characteristic, which is applying filter banks on the image and compute the energy of the filter responses. The methods can be divided into spatial domain, frequency domain, and joint spatial/spatial-frequency domain techniques. Model based methods [8, 9] include, among many others, fractal models, autoregressive models, random field models, the epitome model, and the texem model.

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In this paper we have proposed a new method with some specifications to classify textures. The distribution of pixel properties with gray level greater than or equal to threshold of evaluation and binary image is produced and also the "co-occurrence entropy" is calculated. Thus we'll have the composition of points on the 2-dimentions, one of them is threshold value and the other is "co-occurrence entropy". We can determine some points considered a complex of fractal by these two-dimensions. The other famous criterions could be suggested are: Entropy, Mass Entropy [10] and Hausdroff dimension [11]. Although some of these cases are useful but sometimes difficult to compute that we can calculate it easily and replace it by a modified method. Random threshold vector for texture classification is useful and with one of metrics of distance such as Euclidean distance between image features vector which could be easily categorized.

Table 1: Inexhaustive list of textural analysis methods

Category	**Method**
Statistical	1. Histogram properties 2. Co-occurrence matrix 3. Local binary pattern 4. Other gray level statistics 5. Autocorrelation 6. Registration-based
Structural	1. Primitive measurement 2. Edge Features 3. Skeleton representation 4. Morphological operations
Filter Based	1. Spatial domain filtering 2. Frequency domain analysis 3. Joint spatial/spatial-frequency
Model Based	1. Fractal models 2. Random field model 3. Texem model

3. Methodology

The proposed approach includes two stages. In the first stage the first dimension of feature vector is computing by using a threshold method. After that in the next stage, the second dimension is calculating by using RTV method on the Co-occurrence matrixes which provided of original image. The continuing of this part will describe these stages individually.

3.1. First Dimension (Binary Image)

For the classification method presented in this article, you must first get binary images from Gray level images from the dataset. Obviously, a binary image can be obtained from a grey level image with a threshold value in it grey levels. If N is the count of brightness levels, we can obtain N different binary images from the gray level image. In [12] the authors used a unique threshold method to analysis textures. According to [12], the threshold binary image of a grey level image (I) at threshold (th) is defined by equation (1):

(1)
$$I(x,y) = \begin{Bmatrix} 1 if I(x,y) \geq th \\ 0 if I(x,y) \leq th \end{Bmatrix}$$

A gray level scale is reduced to several binary images and binary images are obtained on the random threshold of a grey level image as stated in equation (2):

(2)
$$th = \mu + (i/n) * k * \sigma$$

As observed in equation (2) μ is the grey level mean and σ2 is the variance of an image I, i is a value between zero and maximum value of grey level Image, k is a value between 0 and 1 that can set by user, Actually threshold by i ,n ,k tune around the point to get acceptable result , to improve the result of algorithm in binary

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images, since the texture of image is distributed around the major area of image we can use small or middle size texture for reduction of computation.

3.2 Second Dimension (RTV of Co-Occurrence Matrix)

When binary images produced, the co-occurrence matrix is used to texture analysis .The method that Computation instruction co-occurrence matrix for a tree level image in three side is shown above :

1	1	0	0
1	1	0	0
0	0	2	2
0	0	2	2

Image I

4	0	2
2	2	0
0	0	2

Cd d=(0,1)

4	0	2
2	2	0
0	0	2

Cd d=(1,0)

2	0	2
2	1	1
0	0	1

Cd d=(1,1)

Figure 1： co-occurrence matrix for a tree level image in three side

As observed, co- occurrence matrix determines the brightness value of distinguished pixel by level (i) from the beside pixel with brightness level (j).
In RTV method, after thresholding, it’s necessary to compute RTV feature. According to the [12], to obtain the RTV vector, Zero run-length matrix (ZRLM) and one run-length matrix (ORLM) is described and used. ZRLM and ORLM are computing by using entropy value of thresholded original image. The results showed its have too complexity and may be don’t provide good accuracy rate. So in this paper the entropy of Co-Occurrence matrixes is described as the second dimension of feature vector.
For computing of second dimension as feature vector it’s sufficient to compute the value of Co-occurrence matrix entropy, and we can obtain it from below formula:

(3)
$$H = -\sum_i \sum_j N_d(i,j)\log_2 N_d(i,j)$$

Where N is the co-occurrence matrix and H is the entropy value. Also "d" shows the direction of Co-occurrence that is computed.
The threshold that we obtained is the first-dimension of feature vector, entropy value of Co- occurrence matrix is the second dimension of feature vector, finally the feature vector contain the threshold value and entropy of co-occurrence matrix.
It's clear that each binary image create one point in feature space, that these points show accurate result in next part.

4-Result:

As it was mentioned in the introduction part, the main aim of this article is to offer a new approach for texture Classification. Thus, to get results and observe the efficiency of proposed approach three kinds of textures name sand, textile and grass 24 images were taken from Brodatz dataset. It means 8 images of every kind of texture. Then, each of images is divided to 4 sub-windows. So, 32 images are provided for every kind. The images have been processed by the approach offered in this article, and the features arecomputed for them according to section 3. Then there has been a dataset made consisting 96 instances, and 2 attributes. Every instance has a label which is the kind of that texture. Finally, by using some of the classifiers such as KNN, NaiveBayes, and LADTree, and by using N.Fold method (N was 10), the accuracy rate of texture classification has been computed, which is shown in the table2. In second and third rows of the table1, the stone textures were classified just based on RTV to compare the proposed approach with some of the previous approaches in term of accuracy. As it is shown in table1, the accuracy of the new approach is much higher than other previous

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approach. The main advantages of the proposed approach in this article can be mentioned in two points. 1- Introducing a series of new features which are able to be computed for different applications. 2- Accurate approach for texture analysis and classification.

Some of the textures are shown in figures2, 3 and 4. Also the entropy values of some of the test images are shown in tables 2,3 and 4 per kind of texture.

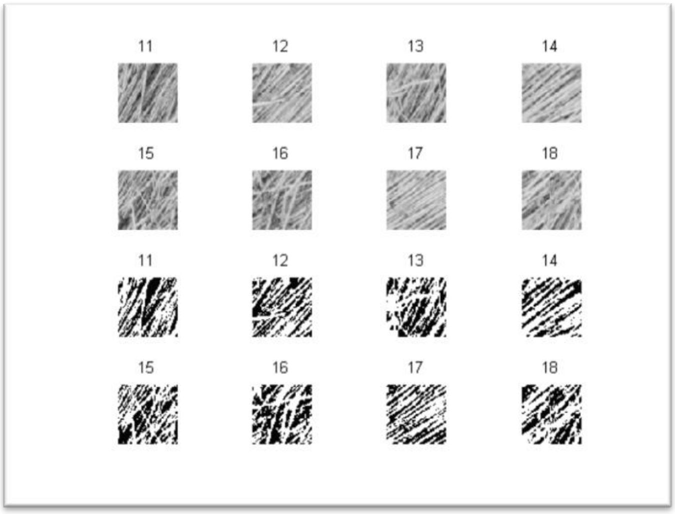

Figure 1：texture images of Grass

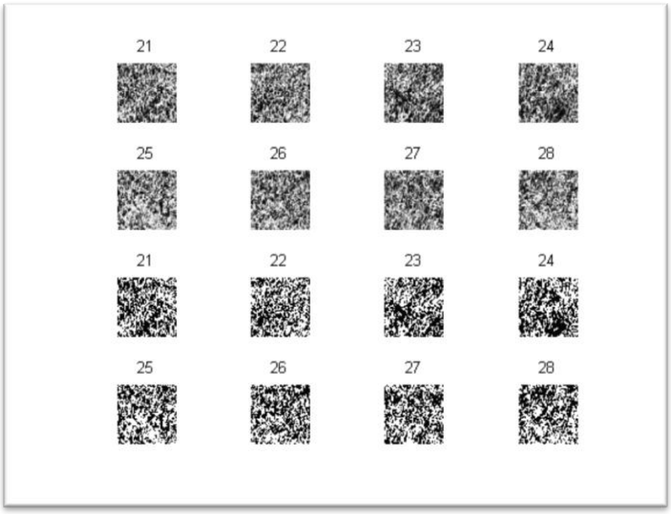

Figure 2：texture images of Sand

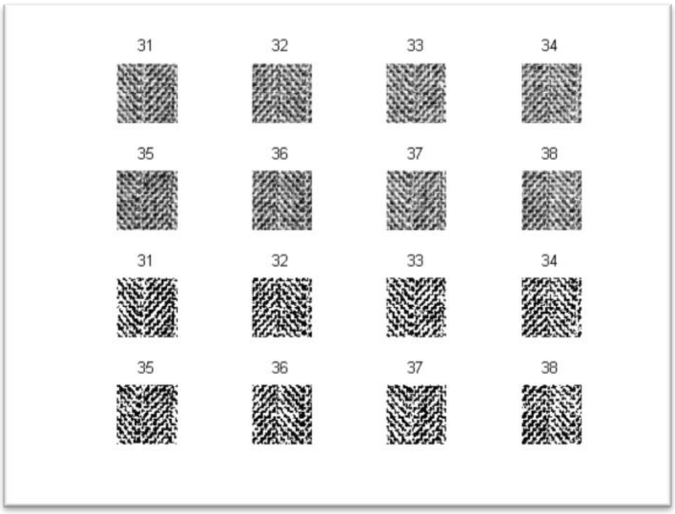

Figure 3：texture images of textile

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Table 2: The accuracy rates of dataset

Classifier	Accuracy Rate ± Std
3 NN	**83.7 ± 0.4**
5 NN	**92.7 ± 0.5**
Naïve Bayes	**93.4 ± 0.2**

Table 3: Threshold And co-occurrence matrix entropy for Grass Textures

Tex. No	***Threshold***	***co-occurrence matrix entropy***
1_1	145	40592
1_2	168	40830
1_3	158	40947
1_4	175	41733
1_5	151	40726
1_6	152	41072
1_7	179	41278
1_8	166	41217

Table 4: Threshold And co-occurrence matrix entropy for Sand Textures

Tex. No	***Threshold***	***co-occurrence matrix entropy***
2_1	122	196800
2_2	122	196880
2_3	110	197410
2_4	113	197360
2_5	137	197480
2_6	125	197470
2_7	119	197610
2_8	133	198160

Table 5: Threshold And co-occurrence matrix entropy for Textile Textures.

Tex. No	***Threshold***	***co-occurrence matrix entropy***
3_1	132	89677
3_2	135	89591
3_3	140	89795
3_4	140	89813
3_5	122	89571
3_6	127	89695
3_7	139	89667
3_8	138	89801

5.-Conclusion

The purpose of this article is offering an approach for texture classification. In this respect, in section 3, by using the threshold method, the texture has been analyzed. After that, by computing Co-Occurrence matrixes and extracting statistical features like RTV, the feature extraction has been done. So, a computable feature vector which has most meaningful information of texture is provided. Then the dataset was made in the result part by using feature vectors which has been extracted from texture images. So, by using classifiers, texture classification was done in test stage.

The results at the end show that the approach which has been proposed in this article has got a high ability and accuracy in texture classification. The main advantages of the proposed approach in this article can be mentioned in two points. 1-Accurate approach for texture analysis and classification 2-Introducing a series of new features which are able to be computed for different applications 3- Computable and low complexity for implementation.

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