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Texture Classification Using Discrete Shearlet Transform

M. Kanchana Research Scholar, Anna University, Chennai, Tamil Nadu, India

Dr. P. Varalakshmi Assistant Professor(Sr.Gr), Madras Institute of Technology, Chennai, Tamil Nadu, India

ABSTRACT

In this paper, an efficient approach for texture classification system based on Discrete Shearlet Transform (DST) is proposed. The classification of texture is achieved by extracting block based energy form the shearlet decomposed image. First, the texture image is decomposed by 2-level DST with 2-direction. Then the proposed block based energy is extracted from each sub-band of the decomposed image. The block size used in the proposed system varies from 4 to 64. These block based energies are used as features to classify the given texture image using robust nearest neighbor classifier. Brodatz database texture images are used to evaluate the proposed system. Experimental results show that the proposed method produces more accurate classification rate for block size 64 is over 94%.

1. Introduction

Texture provides essential information for many image classification tasks. Texture classification is the most important but difficult task in image processing and its applications. Extensive researches have been made for the analysis of texture images and they captured different texture properties to analyze them. It has been widely used in industrial, biomedical, remote sensing areas and target recognition. Approaches to texture feature extraction can be categorized as statistical, structural, model based and filter based methods. Statistical approaches attempt to characterize textures in a probabilistic sense based on definitions such as smooth, coarse, grainy, regular, directional, etc. These characteristics can be measured either spatially or spectrally. Simple statistical measures include the standard deviation, variance, skewness, and kurtosis of the gray levels. More complex measures are those based on GLCM and multi resolution analysis.

The structural approach assumes that the texture is a spatial arrangement of basic primitives. The texture feature extraction can then be done by obtaining measurements of the primitives and their spatial arrangements. The model based approaches are based on random fields and fractal parameters. They usually fit specific models to the textures. The model parameters thus obtained are then used for texture description. A commonly adopted model is the Markov random field. In this study, an approach for the classification of Brodatz texture images based on multi resolution analysis is proposed.

2. Related Works

A completed modeling of the LBP operator is proposed and an associated Completed LBP (CLBP) scheme is developed for texture classification in [1]. Three operators are defined to extract the image local gray level, the sign and magnitude features of local difference, respectively. Gaussian Markov Random Field (GMRF) model is used on linear wavelets for the classification of textures in [2]. They used seven features that are extracted using least square error estimation method on third order Markov neighborhood.

Texture classification by modeling joint distributions of local patterns with Gaussian mixtures is proposed in [3]. Local texture neighborhoods are first filtered by a filter bank. Without further quantization, the joint probability density functions of the filter responses are then described parametrically by Gaussian mixture models (GMMs). A novel texture classification method using patch-based sparse texton learning is presented in [4]. The dictionary of textons is learned by applying sparse representation to image patches in the training dataset. A novel, efficient, and effective refined histogram for modeling the wavelet sub-band detail coefficients and a new image signature based on the refined histogram model for supervised texture classification is described in [5]. An efficient signature extraction algorithm based on the coefficient-counting technique, which helps to speed up the overall classification system performance is also presented. Local Binary Pattern (LBP) algorithm is a typical texture analysis method combined with structural and statistical texture. Completed modeling of Local Binary Pattern is presented in [6], which is composed by the center gray level, sign components and magnitude components.

A new approach to extract global image features for the purpose of texture classification using dominant neighborhood structure is proposed in [7]. Features obtained from the local binary patterns are then extracted in order to supply additional local texture features to the generated features from the dominant neighborhood structure. A texture descriptor algorithm called invariant features of local textures (IFLT) is described in [8]. IFLT generates scale, rotation and (essentially) illumination invariant descriptors from a small neighborhood of pixels around a centre pixel or a texture patch. IFLT is a very robust, efficient and computationally efficient descriptor, which as a fundamental method has a wide range of potential applications in the field of computer vision and image / video processing.

A novel Bayesian texture classifier based on the adaptive model-selection learning of Poisson mixtures on the contourlet features of texture images is proposed in [9]. The adaptive model-selection learning of Poisson mixtures is carried out by the recently established adaptive gradient Bayesian Ying-Yang harmony learning algorithm for Poisson mixtures. Wavelet based image texture classification using local energy histograms are proposed in [10]. An efficient one-nearest-neighbor classifier of texture via the contrast of local energy histograms of all the wavelet sub-bands between an input texture patch and each sample texture patch in a given training set is described. The classification performance of several feature extraction and classification methods for exotic wood texture images are described in [11]. The Gray Level Co-occurrence Matrix, Local Binary Patterns, Wavelet, Ranklet, Granulometry, and Laws' Masks will be used to extract features from the images.

This paper is organized as follows. The introduction about discrete shearlet transform is described in Section 3. The proposed texture classification algorithm based on DST is presented in Section 4. Experimental results are presented in Section 5. The conclusion from the experimental results is made in Section 6.

3. Discrete Shearlet Transform

Shearlets are very similar to curvelets in the sense that both perform a multi-scale and multi-directional analysis. Each basis element has a frequency support that is contained in a rectangle of size proportional to $2^j \times 4^j$ (or $4^j \times 2^j$) in both transforms, which means that the length of the frequency support is approximately the squared width of the frequency support. This property is called parabolic scaling. Hence the frequency supports become increasingly thin as *j* decreases. Both transforms have very similar asymptotic approximation properties, for images $f(x)$ that are C^2 everywhere except near edges, where $f(x)$ is piecewise C^2, the approximation error of are construction with the N -larg-

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est coefficients ($f N (x)$) in the shearlet/curvelet expansion is given by

$$\|f - f_N\|_2^2 \leq B.N^{-2}(log\ N)^3, N \to \infty \quad (1)$$

with B as a constant. Because this is the optimal approximation rate for this type of functions, this property is often referred to as optimal sparsity. Still, there are a number of differences between Shearlets and Curvelets [12].

- ✓ Shearlets are generated by applying a family of operators to a single function, while curvelet basis elements are not.
- ✓ Shearlets are normally associated to a fixed translation lattice, while curvelets are not. This is of importance for applications: when combining information from multiple scales and orientations.
- ✓ In the construction of the shearlet tight frame above, the number of orientations doubles at every scale, while in the curvelet frame this number doubles at every other scale.
- ✓ Shearlets are associated to a multi-resolution analysis, while curvelets are not.
- ✓ The primary advantage is that shearlets allow for a much less redundant sparse tight frame representation, while offering shift invariance.

4 Proposed Method
4.1 Feature Extraction
The block diagram of the proposed feature extraction stage is shown in Figure 1. In the feature extraction stage, the training texture images are decomposed by using 2-level DST with 2-direction. All sub-band images in the shearlet decomposed image are divided into defined block size (S). The block size used in the proposed approach is 4, 8, 16, 32 and 64. For each block the energy is calculated by using the formula

$$Energy_b = \frac{1}{S*S}\sum_{i=1}^{S}\sum_{j=1}^{S}|B_b(i,j)| \quad (2)$$

where $B_s(i,j)$ the pixel value of the b[th] block of the sub-band B and S is the block size. All the block energy are combined together to form the feature vector of the corresponding texture image. Similarly, the proposed features are extracted for all training texture samples and stored in the database for classification.

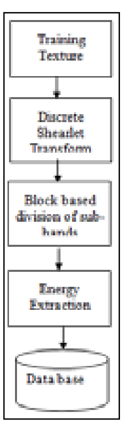

Figure 1 Feature Extraction Stage

4.2 Classification Stage
The nearest neighbor classifier is designed to classify the unknown texture image into known texture class. The distance measure used in the classifier is Euclidean distance.

Let us consider $a = (x_1, y_1)$ and $b = (x_2, y_2)$ are two points. The Euclidean distance between these two points is given by

$$D(a,b) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

The proposed block based energies are extracted from the sub-bands of the shearlet decomposed unknown texture image. Then the extracted unknown features are processed with the features in the stored database. The performance measure of the proposed texture classification system is the classification rate which is measured as the percentage of test set images classified into the correct texture class.

5. Experimental Results
In this section, the performance of the proposed texture classification algorithm based on DST is described. Brodatz texture images are used to evaluate the performance of the proposed system. The size of the Brodatz texture image is 640x 640 pixels and the images are gray scale images. From each original image, totally 256, 128x128 pixel size images are extracted with an overlap of 32 pixels between vertical and horizontal direction. Among the 256 images, 81 images are randomly chosen for the evaluation. 81 images are separated into two set and 40 images are randomly selected as training set and the remaining images as testing set.

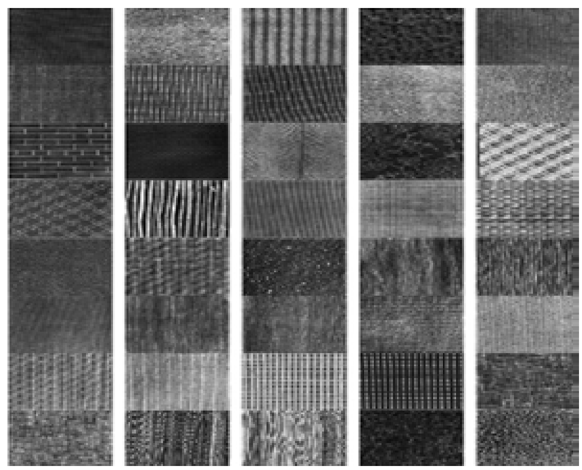

Figure 2 Brodatz texture images used in the proposed classification system

In this experiment, 2-level shearlet transform with 2-direction is used to decompose the texture images. The performance of the proposed system is evaluated by varying the block size from 4 to 64. The proposed block based energy features are extracted based on the block size. Average classification rate of the proposed method for various block size shown in figure 3.

Table 1: Classification rate of the proposed system for various block size

Texture ID	Block Size				
	4x4	8x8	16x16	32x32	64x64
D6	100	100	100	100	100
D9	0	0	2.439	58.537	92.683
D11	97.561	100	100	100	78.049
D16	100	100	100	100	100
D17	46.341	17.073	73.171	100	100
D20	100	100	100	100	100
D21	100	100	100	100	100
D22	17.073	24.390	95.122	90.244	97.561
D24	0	21.951	58.537	100	100
D26	100	100	100	100	97.561
D34	100	100	100	100	100
D36	2.439	2.439	90.244	82.927	73.171
D41	0	0	0	60.976	87.805
D46	92.683	92.683	97.561	100	100
D47	58.537	63.415	92.683	97.561	95.122

D51	82.927	82.927	80.488	58.537	92.683
D53	100	100	100	100	100
D55	92.683	100	100	97.561	97.561
D56	70.732	65.854	70.732	85.366	100
D57	0	0	51.219	97.561	100
D64	48.780	60.976	80.488	85.366	97.561
D66	0	0	29.268	95.122	97.561
D68	19.512	34.146	68.293	97.561	100
D76	41.463	46.341	36.585	24.390	58.537
D77	100	100	100	97.561	97.561
D78	97.561	85.366	92.683	97.561	100
D79	75.610	90.244	90.244	90.244	92.683
D80	0	0	53.658	60.976	75.610
D82	87.805	97.561	87.805	97.561	100
D83	100	100	100	100	87.805
D85	100	100	92.683	85.366	87.805
D101	87.805	100	100	100	100
D102	92.683	97.561	95.122	100	92.683
D103	0	0	4.878	75.610	87.805
D104	2.439	14.634	92.683	100	100
D105	78.049	95.122	100	100	100
D106	100	100	100	97.561	97.561
D109	0	0	0	60.976	95.122
D111	0	0	0	24.390	95.122
Avg.cla. rate	58.7867	61.3508	75.2971	87.6798	94.2464

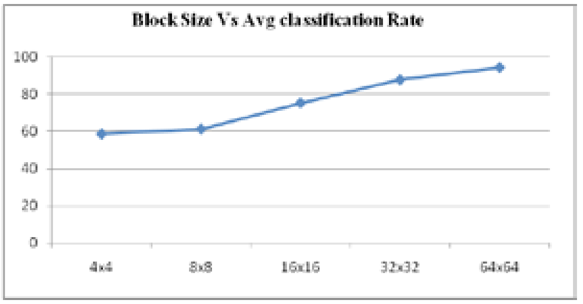

Figure 3 Average classification rate of the proposed method for various block size

6. Conclusion

In this paper, DST based classification of Brodatz texture images is presented. The proposed method decomposes the texture images by 2-level DST with 2-direction.The proposed block based energies of each sub-band is calculated. These energies are used as features for classification. The size of the block is varied to evaluate the performance of the proposed system. Experimental results show that the proposed system achieves 94.25% for block size of 64. As the size of the block increases, the classification rate of the proposed system also increases. In future, the classification rate of the proposed system may be increased by varying the decomposition level and directions.

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