VOL. 10, NO. 11, JUNE 2015 ISSN 1819-6608

ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

TEXTURE CLASSIFICATION USING MULTIRESOLUTION TRANSFORMS

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ABSTRACT

Classification refers to assigning a physical object into one of the predefined categories. In texture classification, the goal is to assign an unknown sample image to one of a set of known classes. Texture classification is one of the challenging problems in image processing and computer vision. A major problem in textures in real world is often not uniform, due to changes in orientation, scale or other visual appearance. In addition, the degree of computational complexity of many of the proposed texture measures is very high. Important application of the texture classification include industrial and biomedical surface inspection, for example defects and disease, ground classification and segmentation of satellite or aerial imagery, segmentation of textured region in document analysis, and content based access to image databases. In this project an efficient method of texture classification using multi resolution transforms (Non Sub sampled Contourlet Transform) is proposed, which considers the features of texture images. Non Subsampled Contour let Transform has been widely recognized as a very useful tool in texture analysis, due to its optimal localization properties in both directional and frequency domain. The features (mean, standard deviation) are extracted from Non sub sampled Contourlet transform sub bands. The experimental result 85.79% achieved the classification rate of the proposed texture classification systems.

Keywords: texture classification, computer vision, pattern recognition, feature extraction, non sub sampled contour let transform.

1. INTRODUCTION

The texture is defined as a spatial variation in pixel intensities is often referred to as texture. Texture analysis is a major role of machine vision and image processing. It is generally divided into four canonical areas such as Classification, Segmentation, Synthesis, and Shape from texture. The texture classification can be done by features extraction that differentiates the textures. Texture classification can be classified as follows, statistical methods, model based methods, structural methods, and filter based or signal processing method. Chen et al (1998) defined that the goal of texture classification is to produce a classification map of the input image where each uniform textured region is identified with the texture class it belongs. The second type of problem in texture analysis is texture segmentation. It is partitioning of an image into regions which have homogeneous properties with respect to texture. Texture synthesis is used for image compression applications. The goal of texture synthesis is to model a image texture, which can be used for generating the texture. Shape from texture is one instance of a general class of vision problems. The three dimensional shape information is extracted from various cues.

Texture classification deals with texture analysis techniques such as synthesis, classification, segmentation and shape from texture [1]. Texture analysis is used in many applications like identifying manufacturing defects, disease diagnosis, ground classification and rain forecasting using satellite images, document analysis, face detection, fabric classification [2] and content based access to image retrieval. Texture classification is used to two phases are in namely the learning phase and the recognition phase. In learning phase, the textural features are represented by scalar numbers which describe the various properties of the images, such as spatial structure, contrast, roughness, orientation, etc. In the recognition phase, the same method is applied to extract the texture content of the unknown samples. Then these features are compared with the training images and the sample best matched is assigned to that category [3]. Texture describe the statistical or structural relationship between pixels, and it provide details of various properties of image such as contrast, smoothness, coarseness, randomness, regularity, linearity, directionality, periodicity, and structural complexity. Image classification is one crucial step in the broader area of image analysis [4]. There are varieties of feature extraction methods exist based upon signal processing or filtering techniques [5]. Using statistical approaches, several schemes have been suggested right from co-occurrence matrix, run length matrix based, auto correlation, auto regression, Markov Random Fields based, moments based etc. [6]. Textures could be graded as coarse, micro, macro, regular, periodic, a periodic, Directional, random, or stochastic [7]. This paper is organized as follows. Literature survey is given in Section II. Section III is about Non Subsampled Contourlet Transform. Section IV is about Experimental study, Conclusion in Section V and finally References are in Section VI

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2. LITERATURE SURVEY

Hong *et al.* assumed that edge pixels from a closed contour, and primitives were extracted by searching for pixels with opposite directions, followed with a region growing operation. Properties of the primitives (e.g. area and average intensity) were used as texture features [8].

Kaiser(1995) have explained about statistical method which analyze the spatial distribution of gray values by computing local features at each point in the image, and deriving a set of statistics from the distribution of local features. This method also includes autocorrelation, which has been used for analyzing the regularity and coarseness of texture include autocorrelation function [9].

Texture classification method using the Non Sub sampled Contour let transform (NSCT) and support vector machines (SVMs) is carried out. The NSCT provides a shift-invariant, multi scale, and multidirectional image representation that have proven to be very efficient in image analysis applications. Features are extracted from NSCT coefficients of source images and SVMs, are used as classifiers for texture classification [10].

In our proposed system, Non Sub sampled Contour let Transform is applied to extract the high dimensional features, which is enormously present in textures. Non sub sampled Contour let transform decomposes the input image into many sub bands. The features are extracted from Nonsubsampled Contourlet transform sub bands. The minimum distance classifiers are used for classification.

3. NON SUBSAMPLED CONTOURLET TRANSFORM

In this work, Nonsubsampled Contourlet transform (NSCT) is applied to extract the features from the textures. The shift invariance property of NSCT is very effective in extracting texture features. It is a modified version of Contourlet transform (CT) to avoid the frequency aliasing problem and to enhance directional selectivity and shift invariance. The contourlet transform (CT) is proposed by Do and Vetterli [4]. The CT has the ability to capture smooth contours of the images. The Contourlet Transform consists of two dimensional filter bank such as laplacian filter bank and directional filter bank. Laplacian pyramid to capture the point discontinuities and directional filter bank to link the point discontinuities into linear structure. Laplacian Pyramid is used for multiscale decomposition and the Directional filter bank for directional decomposition. The contourlets satisfy the anisotropy property and can capture intrinsic information of images like edges and contours, which helps in attaining better representation than discrete wavelet transform. But, the CT lacks in shift invariance property because of the downsampling and upsampling effect.

The NSCT developed by Cunha, Zhou, and Do mainly focus to avoid the frequency aliasing problem and enhances directional selectivity and shift-invariance. The construction of NSCT is a double filter bank, which combines nonsubsampled pyramid for multiscale and nonsubsampled directional filter bank structure for directional decomposition. Initially, the nonsubsampled pyramid split the input image into low pass and high pass sub band. Then a nonsubsampled DFB is applied to decompose the high pass sub band into several directional sub bands by increasing the number of directions with frequency. This step is repeatedly iterated on the low pass sub band. In NSCT the multiresolution decomposition is done by shift invariant filter banks which satisfy bozout identical equation. The low pass sub band has no frequency aliasing effect because, of no downsampling in the pyramidal decomposition level. Hence the bandwidth of low pass filter is larger than π /2. The NSCT has better frequency characteristics than the CT. The perfect reconstruction condition is given as

$$H0\,(z)\,G0\,(z) + H1\,(z)\,G1\,(z) = 1 \tag{1}$$

Since, this condition can be easily satisfied than the perfect reconstruction condition for critically sampled filter banks, it is possible to design better filters.

In Figure-1 the two level decomposition of NSCT is shown, which provides multi scale, multi direction, and shift invariant image decomposition. The NSCT is the non separable two-channel filter bank composed of basis function oriented at various direction in multiple scales, with different aspect ratios. With this rich set of basic functions, it captures smooth contours that are the dominant feature in texture effectively. Since the NSCT has desirable properties of shift invariant, it is used to extract features from the texture images.

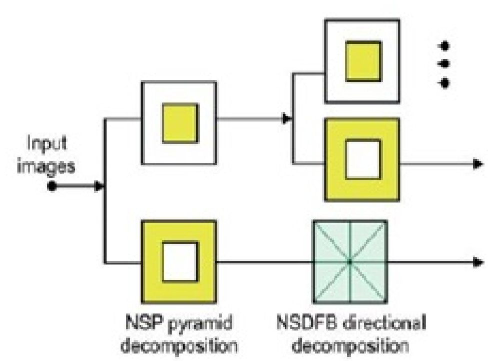

Figure-1. Construction of NSCT.

4. EXPERIMENTAL STUDY

The database is decomposed by Nonsubsampled Contourlet Transform. The features like mean and standard deviation are extracted from Non Subsampled Contourlet Transform sub bands. Then the minimum distance value is calculated. Then the texture is classified using the minimum distance value.

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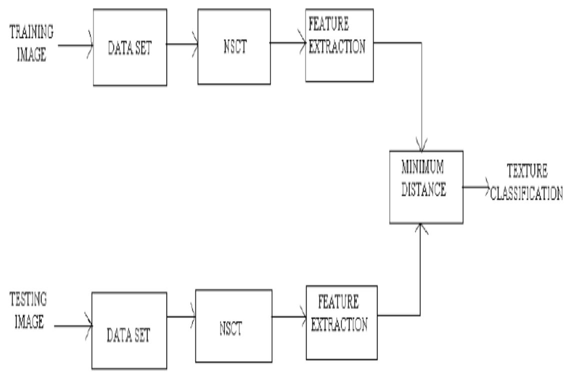

Figure-2. Flow chart of the proposed method.

The experiments are conducted by using Brodatz texture album. The Brodatz database is well known and widely used as benchmark datasets in texture classification. It is consists of 112 textures that were abstracted from the Brodatz texture album. For the experiment purpose, 13 classes of size 512 x 512 are taken. Each of these textures is produced from a single image scanned from the texture album. In Brodatz texture dataset all the textures are represented by a single image.

The Texture image is decomposed into eight sub bands by the Nonsubsampled Contourlet transform at four different resolution levels, at each resolution level it is decomposed into 2^n sub bands where n = 0,1,2,3,4.... is the order of the directional filter. Since the order is 3, the input image is decomposed into 8 sub bands. As the transform is nonsubsampled therefore each resolution level corresponds to the actual size of texture image input i.e. 512x512.

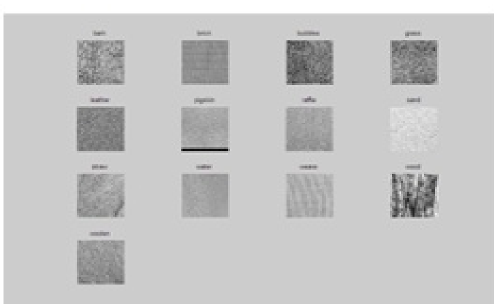

Figure-3. Brodatz images used in experiments.

The texture image is decomposed into eight sub bands by the Nonsubsampled Contourlet transform at four different resolution levels, at each resolution level it is decomposed into 2^n sub bands where n = 0,1,2,3,4.... is the order of the directional filter. Since the order is 3, the input image is decomposed into 8 sub bands. As the transform is nonsubsampled therefore each resolution level corresponds to the actual size of texture i mage input i.e. 512x512. Then features are extracted from the Nonsubsampled Contour let Transform sub band.

a) The approximation coefficient for decomposed bark image

The Non Sub sampled Contour let transform is applied to the 13 images from brodatz album. The original Brodatz bark image is shown Figure-3 In this work, Non Sub sampled Contour let transform is used with parameter values like lower center frequency, upper center frequency for different resolution level of coefficient. The texture images are decomposed into Approximation Coefficient and detail Coefficient. The bark image approximation output Figure-4 is given.

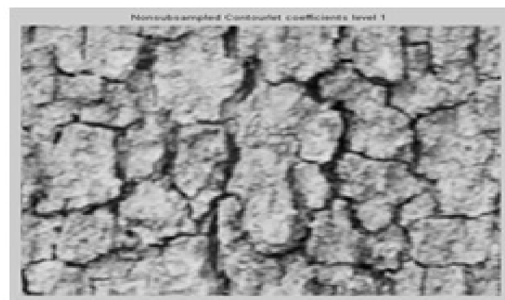

Figure-4. Approximation output.

b) The detail coefficient for decomposed bark image

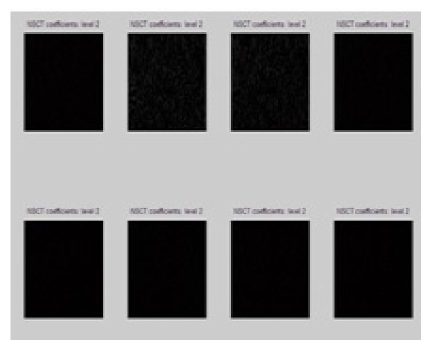

Figure-5. Detail coefficient output.

$$M_k = \frac{1}{W \times H} \sum_{i=0}^{W-1} \sum_{j=0}^{H-1} \left(I_k(i,j) \right) \quad (2)$$

$$\sigma_k = \sqrt{\frac{1}{W \times H} \sum_{i=0}^{W-1} \sum_{j=0}^{H-1} (I_k(i,j) - M_k)^2} \quad (3)$$

$$D(f_{test}, f_{lib}) = \sqrt{\sum_{i=1}^{N} \left(f_{(test)_i}(x) - f_{(lib)_i}(m) \right)^2} \quad (4)$$

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From equations (2),(3),(4) Nonsubsampled Contourlet Transform features like mean, standard deviation and minimum distance can be found out.

Classification rate=correctly classified image/total image

Table-1. Classification result for same size images.

Image Name	Mean	Standard deviation	Classification rate (%)
bark	160.8138	64.8347	100
brick	146.0613	21.56272	100
bubbles	120.8709	56.0191	100
grass	149.0192	80.9366	100
leather	146.7789	62.7589	100
pigskin	165.8281	55.029	100
raffia	166.2638	42.5701	100
sand	222.9045	39.637	100
straw	169.5079	59.3274	100
water	165.3003	23.375	100
Weave	185.5343	46.3556	100
wood	151.9898	104.9776	100
woolen	156.9953	42.5876	100

c) Divides the input images into 4 equal sub images

Each 512×512 image of texture classes is divided into 4 non overlapping 256×256 sub images. There are 52(4×13) texture sub images in the experiment database. The Figure-6 shows the sub divided images for bark image into four equal sizes (256×256). Then the subdivided images by Non Subsampled Contourlet Transform are decomposed.

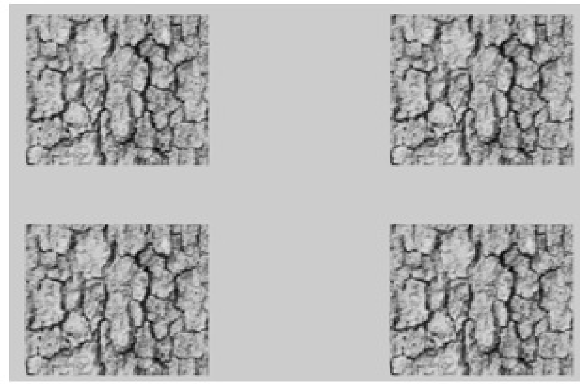

Figure-6. Subdivide the image four equal size.

d) Divides the input images into 16 equal sub images

Each 512×512 image of texture classes is divided into 16 non overlapping 128×128 sub images. There are 208(16×13) texture sub images in the experiment database. Figure-7 shows the bark image is sub divided into sixteen equal sizes (128×128). Then the subdivided image by Nonsubsampled Contourlet Transforms are decomposed image the features like mean and standard deviation are found and its texture is classified.

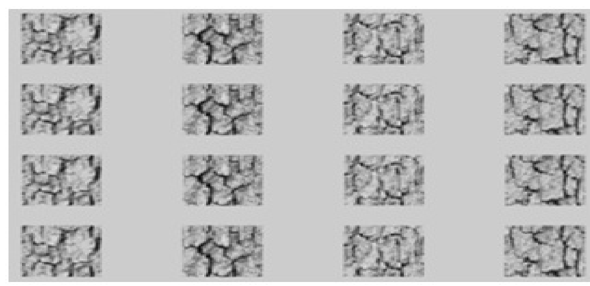

Figure-7. Subdivide the image sixteen equal size.

Table-2. Detailed results of Brodatz Album for texture classification using Nonsubsampled Contourlet Transform.

Image Name	Mean classification Rate (%)	Standard deviation Classification Rate (%)	Mean+ Standard deviation Classifica tion Rate (%)
bark	23.07	38.46	100
brick	92.30	100	100
bubbles	92.30	76.92	46.15
grass	61.53	100	92.30
leather	23.07	100	100
pigskin	61.53	46.15	92.30
raffia	38.46	38.46	92.30
sand	100	100	100
straw	84.61	23.07	53.84
water	23.07	61.53	100
Weave	100	23.07	92.30
wood	53.84	100	84.61
woolen	15.38	30.76	61.53

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Table-3. Consolidated result for texture classification using Nonsubsampled Contourlet Transform.

Features	Classification Rate (%)
Mean	59.16
Standard Deviation	64.49
Mean + standard deviation	85.79

5. CONCLUSIONS

From the experimental analysis it is inferred that the proposed feature set produces 85.79% classification rate. This method is done with 13 natural Brodatz texture images. The success rate obtained for Non sub sampled Contourlet Transform is achieved. These images are used for texture classification.

6. FUTURE WORK

The proposed work can be extended by using Zernike moments and various other classifier like KNN, SVM etc. Also, the levels of decomposition can be increased to obtain several subbands to extract its features to a generate extent.

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