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Texture Image Classification Using Nonsubsampled Contourlet Transform and Local Directional Binary Patterns

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Abstract— Texture is a rich source of visual information about the surface characteristics of an object in the digital image. So texture characteristics play an important role in texture image classification. In this paper, we propose a novel approach of texture image classification based on nonsubsampled contourlet transform (NSCT) and local directional binary patterns (LDBP). The NSCT has translation invariability and LDBP has rotational invariance. The feature set is obtained by applying LDBP approach and co-occurrence parameters for three level NSCT subbands. The principal component analysis (PCA) is used to reduce the dimensionality of feature set. The class separability is enhanced using linear discriminant analysis (LDA). The features obtained from LDA are representatives of each texture class. The classification performance is tested on a set of 16 Brodatz textures. The k-NN classifier is used for classification. The experimental results demonstrate that the proposed method performs better than existing methods in the reduced feature set.

Keywords— Nonsubsampled contourlet transform, Local directional binary pattern, Principal component analysis, Linear discriminant analysis, Texture.

I. INTRODUCTION

Textures can be regarded as the visual appearance of surfaces. These may be perceived as being directional or non-directional, smooth or rough, coarse or fine, regular or irregular, etc. The surface characteristics of textures can be used to recognize objects in an image, to segment an image and to understand an image. So texture plays an important role in many image analysis, computer vision and pattern recognition tasks. However, environment and illumination conditions can affect the appearance of textures and thus complicate the task. Hence, the texture classification is still considered an interesting but difficult problem in image processing domain. Many of the texture based methods have been proposed for feature extraction. In the early 70's, Harlick et al. [1] have proposed co-occurrence matrix to represent texture features. This approach explored gray level spatial dependency of texture. The tonal variation along a predefined displacement vector is reordered and used to extract texture features such as energy, entropy, contrast, homogeneity or correlation. Tamura et al. [2] have explored texture representation for various angles and proposed a computational approximation on six visual properties, namely, coarseness, contrast, directionality, likeliness, regularity and roughness. In the 90's, the wavelet transform was introduced for texture representation. Smith and Chang [3], [4] used the statistics such as mean and variance extracted from wavelet subbands for texture representation. Thyagrajan et al. [5] have combined wavelet transform with co-occurrence matrix to take the advantage of statistical and transform based features for texture analysis. Ojala et al. [6] have presented a theoretically very simple, yet efficient, multiresolution approach. The approach is tested on gray scale images using rotation invariant texture classification based on local binary patterns (LBP). This method is based on uniform local binary patterns and their occurrence histograms, as powerful texture features. It characterizes spatial configuration of local image texture. Further, the performance can be improved by combining texture features with rotation invariant variance measures.

Most of the textural classification applies spatial information. Spatial classification can be categorized into three groups: (i) statistical approach such as co-occurrence probabilities, (ii) structural approach in which texture is viewed as many primitive elements such as texton or texture unit and (iii) model based approach such as Gaussian Markov random fields and Gibbs random fields. Here texture image is modeled as a probability model or linear combination of set of basic functions and the coefficients of these models are the textural features.

The weakness of all these texture analysis schemes is that the image is analyzed at one single scale. This limitation can be overcome by adopting multiscale representation of the image for texture analysis. Wavelet and wavelet packet methods are widely used. Laine and Fan [7] have implemented various subband decomposition successfully in texture analysis. Arivazhagan and Ganeshan [8] have used wavelet statistical features (WSF) effectively for texture characterization and classification. Hiremath and Shivshankar [9] have used co-occurrence matrix method to extract textural features of multiresolution images. The features are obtained by two level wavelet decomposition in which features are computed by decomposing only the detail subband images. The discrete wavelet transform (DWT) has been successfully applied for a wide range of image analysis problem for two dimensional images. It tends to ignore the smoothness along contours [10]. In addition, the DWT provides only limited directional information which is an important aspect of multidimensional signals [11]. These limitations have been partially addressed by the contourlet transform (CT) which can effectively approximate a smooth contour at multiple resolutions. The CT offers a multiscale and directional decomposition providing anisotropy and directionality features, missing from DWT [10]. The CT is successfully used in variety of texture analysis applications that includes SAR and natural image classification [12], image denoising [13], image compression [14], etc.

Contourlet transform can be divided into two main steps, namely, Laplacian pyramid (LP) decomposition and directional filter bank (DFB). Due to downsamplers and upsamplers present in both LP and DFB, contourlet transform is not shift variant [11]. To achieve the shift invariance, a nonsubsampled contourlet transform (NSCT) was proposed in [15]. It is built upon nonsubsampled pyramids and nonsubsampled DFB. Thus NSCT is fully shift invariant, multiscale and multidirectional image decomposition. The NSCT is used in variety of texture classification problems. Vijilious and Bharathi [16] have implemented texture classification using reduced set of NSCT. In this work, a nonsubsampled contourlet transform is employed to extract the directional frequency information followed by the statistical moment extraction where Zernike moments are used as texture descriptors. This approach reduces the dimensionality for contourlet coefficient. For the experimentation, Brodatz database of textures and nearest neighborhood classifier are used. Liu et al. [17] have proposed NSCT for texture feature extraction, in which mean and standard deviation of NSCT coefficients matrix are computed. The least square support vector machine (LS-SVM) classifier is employed to realize the automatic texture classification. Wang et al. [18] have proposed a texture image segmentation algorithm based on NSCT and SVM. Texture features of image are extracted by decomposing the image using NSCT and classifying the image features using k-NN classification algorithm and training support vector machine. Segmentation is done by means of SVM. Zhao et al. [19] have presented an approach of texture image classification based on nonsubsampled contourlet transform, local binary patterns and SVM. Nonsubsampled contourlet transform and local binary patterns are used to extract texture features of images. Support vector machines are used to classify images. In the literature, the two phase framework of Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) is found to be efficiently used in pattern recognition [20].

In this paper, we propose a new method for texture image classification using nonsubsampled contourlet transform and local directional binary patterns (LDBP) for texture feature extraction. Nonsubsampled contourlet transform has translation invariability, whereas LDBP has rotational invariance. To reduce the dimensionality of feature set and increase the class seperability, the PCA-LDA combination is employed. The classification is performed using k-NN classifier. The experimental results show the effectiveness of the proposed method.

II. NONSUBSAMPLED CONTOURLET TRANSFORM

The nonsubsampled contourlet transform (NSCT) comprises two levels. The level-1 consists of nonsubsampled pyramid structure (NSP) that ensures the multiscale property. The level-2 consists of nonsubsampled directional filter banks (NSDFB) that gives directionality [15]. The NSCT has the properties, namely, anisotropy, shift invariance, multiscale and multidirectional expansion, that has better directional frequency localization, fast implementation without down samplers and up samplers in it. The two level NSCT decomposition is illustrated in the Fig. 1(a). The set of filters that split the 2D frequency plane into subbands are shown in the Fig. 1(b).The nonsubsampled Laplace pyramid is a two channel nonsubsampled filter bank. The perfect reconstruction is achieved provided the filters satisfy the Bezout identity, given by the Eq. (1).

$$H_0(z)G_0(z) + H_1(z)G_1(z) = 1 \tag{1}$$

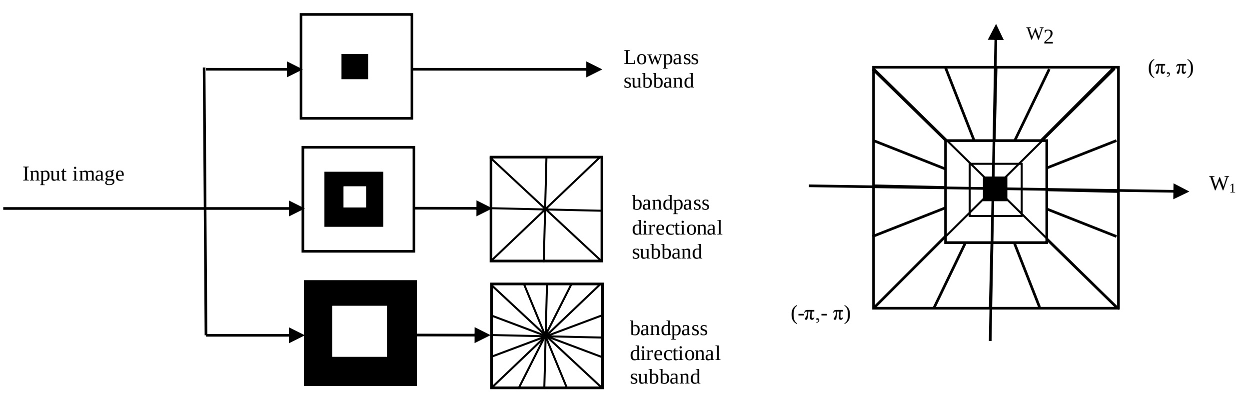

Fig. 1 Nonsubsampled contourlet transform (a) Nonsubsampled filter bank structure that implements the NSCT (b) Idealized frequency partitioning [15].

III. LOCAL DIRECTIONAL BINARY PATTERNS

The most important properties of local directional binary patterns (LDBP) are tolerance against illumination changes and computational simplicity. It extracts local information of texture image. The LDBP transforms signals from spatial representation into frequency representation. An image in LDBP is represented as a sum of sinusoids of changing magnitudes and frequencies. Lower frequencies are more frequent than higher frequencies in a particular image. Image is transformed into its frequency component and gives away lot of higher frequency coefficients than the amount of data needed to describe the image. It can be reduced without compromising on image quality. Most of the visually significant information about the image is only concentrated in just a few coefficients and LDBP makes use of this property.

The basic idea of LDBP is that, 3x3 kernel of image can be treated as basic texture region. The gray value of central pixel is compared with the gray values of eight pixels around it. The central gray pixel value is the threshold value. If the gray value of surrounding pixel is larger than gray value of central pixel, the surrounding pixel is marked as one otherwise zero. The binary values of all surrounding pixels can be obtained. All surrounding pixels are given different metrics. The metrics is multiplied with a binary value of surrounding pixels. Further the sum of product of binary value and metrics of all surrounding pixels is set as the value of local directional binary pattern of central pixel. The value of local directional binary patterns of all pixels in image can be obtained through such calculation neglecting the pixels of edges.

Local texture distribution T can be treated as joint distribution function of all pixels in local texture region. T is represented as given in the Eq. (2)

$$T = t\left(f_c; f_0, f_1, \cdots, f_j, \cdots, f_7\right) \tag{2}$$

where f_c is gray value of the central pixel of local texture region, f_j is the gray value of j^{th} surrounding pixel of local texture region. The factorized joint distribution of the difference of central pixels and each pixel in neighborhood can be represented by the Eq. (3)

$$T = t\left(f_c\right)\ t\left(f_0 - f_c, f_1 - f_c, \cdots\cdots, f_7 - f_c\right) \tag{3}$$

If gray value of central pixel is independent of the difference between the value of the surrounding pixel and central pixel, $t\left(f_i\right)$ can be represented by the Eq. (4)

$$T \approx t\left(f_0 - f_c, f_1 - f_c, \cdots\cdots, f_7 - f_c\right) \tag{4}$$

The Fig. 2 depicts the transformation of neighborhood pixels to calculate central pixel weight in LDBP.

83	83	98
40	80	84
126	94	130

(a)

1	1	1
0		1
1	1	1

(b)

$\cos(135^0)$	$\cos(90^0)$	$\cos(45^0)$
$\cos(180^0)$		$\cos(0^0)$
$\cos(225^0)$	$\cos(270^0)$	$\cos(315^0)$

(c)

-0.7071	0	0.7071
0		1
-0.7071	0	0.7071

(d)

-	-	-
-	1	-
-	-	-

(e)

Fig. 2 Transformation of neighborhood pixels to calculate central pixel weight in LDBP. (a) 3X3 window of image, (b) Binary representation after thresholding, (c) Metrics for 3X3 window, (d) Resultant weights after multiplying corresponding elements of (b) and (c), (e) Final weight of central pixel.

The pixel value can be zero or one. The T can be further represented by using the Eq. (5)

$$T \approx t\left(v\left(f_0 - f_c\right), v\left(f_1 - f_c\right), \cdots\cdots, v\left(f_7 - f_c\right)\right) \tag{5}$$

where

$$v(x) = \begin{cases} 1 & x \geq 0, \\ 0 & x < 0. \end{cases} \tag{6}$$

The LDBP weight can be calculated using the Eq. (7),

$$f_b(x_c, x_c) = \sum_{j=0}^{7} v(f_j - f_c)\cos(j * 45) \quad (7)$$

IV. PCA-LDA

The technique computes the principal component of a sequence of vectors by estimating covariance matrix. It computes linear discriminant directions along which the classes are well separated. Principal component analysis (PCA) is used for dimensionality reduction where as linear discriminant analysis (LDA) is used for enhancing the class seperability. The PCA is used to find a subspace, whose basis vectors correspond to the maximum variance direction in original space. The LDA method searches for the vectors in underlying space that best discriminate among classes. The LDA creates a linear combination of features of data which gives largest mean difference between the desired classes. For all classes, the following two measures are calculated using the Eqs. (8) and (9):

(i) Within class scatter matrix:

$$S_w = \sum_{j=1}^{C} \sum_{i=1}^{N_j} \left(y_i^j - \mu_j\right)\left(y_i^j - \mu_j\right)^T \quad (8)$$

where y_i^j is i^th sample of class j. μ_j is the mean of class j. C is the number of classes. N_j is number of samples in class j.

(ii) Between class scatter matrix:

$$S_b = \sum_{i=1}^{C} \left(\mu_j - \mu\right)\left(\mu_j - \mu\right)^T \quad (9)$$

where μ represents mean of all classes.

The objective is to maximize the between class measure while minimizing the within class measure. i.e. $\max\left(S_b / S_w\right)$

V. PROPOSED METHOD FOR TEXTURE IMAGE CLASSIFICATION

The proposed method for texture image classification consists of two modules, namely, texture training module and classification module. The Fig. 3 shows the block diagram of the proposed method.

A. *Texture Training Module*

The two feature sets are proposed for feature extraction, namely, (i) Harlick features and (ii) Mean and Standard deviation. For the purpose of training, 16 texture classes, each with an image of size 256x256, are considered. Each texture image is divided into 16 equal sized non overlapping blocks of size 64x64, out of which 8 randomly chosen blocks are used as the training samples and remaining blocks are used as the test samples for each texture class. Each block of image is decomposed into three levels by nonsubsampled contourlet transform. The Harlick features, namely, contrast, energy, entropy, homogeneity, maximum probability, cluster shade and cluster prominence, are extracted from each NSCT subband (15 numbers) to obtain the feature set F1. The LDBP weights of each block are calculated, which form the feature set F2 containing 3844 features (=62*62, since image edges are excluded). The steps of the proposed method are given in the Algorithm 1.

Algorithm 1: Training algorithm

Step 1: Input the training image block I of size 64x64

Step 2: Apply NSCT method to image I.

Step 3: Compute Harlick features (7 numbers) from each of the NSCT subbands (15 numbers) to obtain feature vector F1 with 105 (=7*15) features.

Step 4: Compute LDBP weights for image I to obtain feature vector F2 with 3844 features (=62*62, since the image edges are excluded)

Step 5: Form the feature vector F=(F1, F2), which contains 3949 (=105+3844) features and store F in the feature database.

Step 6: Repeat the Steps 1-5 for all the training blocks of all the texture class images and obtain the training set (TF) of feature vectors.

Step 7: Apply PCA on training feature set (TF) of Step 6 to obtain reduced feature set (TFPCA).

Step 8: Apply LDA on reduced feature set (TFPCA) of Step 7 to obtain the discriminant feature set (TFLDA). Store TFLDA in the feature library, which is to be used for texture classification. Denote TFLDA vector as $f_{(lib)}$ vector.

Step 9: Stop

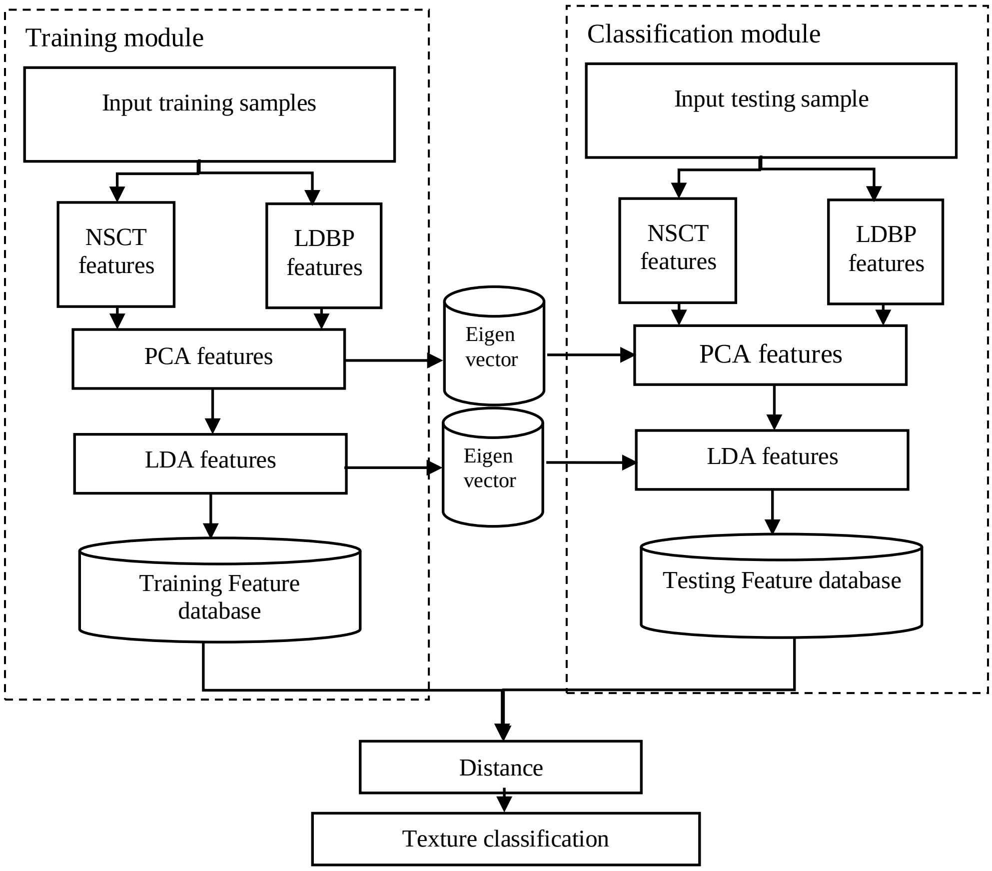

Fig. 3 Block diagram of the proposed method

Further, the above algorithm is implemented using the features, mean (μ) and standard deviation (σ) of pixel values, instead of Harlick features in the Step 3, for the sake of comparison. The experimentation has been done with both types of feature extraction.

B. Texture Classification Module

If $f_{(test)}(x)$ is the feature vector of test sample image x and $f_{(lib)}(m)$ is the feature vector of the m[th] class in the feature library, then the Euclidean distance between these two vectors is given by the Eq. (10) :

$$D(f_{test}, f_{lib}) = \sqrt{\sum_{i=1}^{N} \left(f_{(test)i}(x) - f_{(lib)i}(m) \right)^2} \tag{10}$$

where N is the number of features in the feature vector. The image x is classified using the k nearest neighbor (k-NN) classifier [21]. In k-NN classifier, the class of the test sample is decided by the majority class among the k nearest neighbors. A neighbor is decided to be nearest if it has the smallest distance in the feature space. In order to avoid a tied vote, it is preferable to choose k to be an odd number. The experiments are carried out using k-NN classifier with k=3. The testing algorithm is given in the Algorithm 2.

Algorithm 2: Testing algorithm (Classification of test images)

Step 1: Input the testing image block I_{test} of size 64x64

Step 2: Apply NSCT method to image I_{test}.

Step 3: Compute Harlick features (7 numbers) from each of the NSCT subbands (15 numbers) to obtain feature vector $F1_{test}$ with 105 (=7*15) features.

Step 4: Compute LDBP weights for image I_{test} to obtain feature vector $F2_{test}$ with 3844 features (=62*62, since the image edges are excluded)

Step 5: Form the feature vector F_{test} =($F1_{test}$, $F2_{test}$), which contains 3949 (=105+3844) features and store F_{test} in the feature database.

Step 6: Project F_{test} on TFPCA components and obtain the weights $F_{testPCA}$ which are considered as test image features.

Step 7: Project $F_{testPCA}$ on TFLDA components and obtain the weights $F_{testLDA}$ which are considered as reduced test image features. Denote $F_{testLDA}$ as $f_{(test)}$.

Step 8: (Classification) Apply k-NN classifier (k=3) to classify the test image I_{test} as belonging to class m (m=1, 2,..., 16) using Euclidean distance defined by Eq. (10).

Step 9: Stop

VI. EXPERIMENTAL RESULTS AND DISCUSSION

A. Image Dataset

For experimentation, the texture images are taken from Brodatz album [22]. Each Brodatz sample represents one texture class. Sixteen Brodatz textures are chosen for classification and are shown in the Fig. 4. Each Brodatz texture is of 256x256 pixels with 256 gray levels. These Brodatz textures include regular textures D16, D21, D24, D3, D36, D4, D68, D75, nonregular textures D104, D11, D29, D71, D82 and highly regular textures D51, D52, D6. Each image of a texture class is divided into 16 non overlapping blocks of 64x64 pixels. Thus, 256 blocks are considered. The image data and textures may be artificial or natural, obtained in a real world application. The availability and quality of the ground truth associated with the image is an important part for the selection of image data in the Brodatz. Each image represents the texture category, according to ground truth. Hence, Brodatz textures are used to evaluate the performance of the proposed technique for texture feature extraction and classification. The images are often limited in terms of number of original source images available, so the partitioning of the image into sub images increases the amount of image data set. The images in the data set have different gray scale properties. In order to estimate the performance of texture classification, partitioning of the images into training and testing sets should be independent; the images are randomly divided into separate training and testing sets. The 50% of the subimages are considered as training set and remaining 50% subimages are used for testing. The feature values between training and testing sets proves the basis for quantitative performance analysis.

B. Experimental Results

The experimentation of the proposed method is carried out on Intel® Core™ i3-2330M @ 2.20 GHz with 4GB RAM using MATLAB 7.9 software. The NSCT is performed upto three levels. Further, the features for each level are derived using gray level co-occurrence matrix (GLCM) for distance vector $d(i, j)$ with offset $d(0,1)$. From the GLCM, Harlick texture features, namely, energy, entropy, homogeneity, maximum probability, cluster shade and cluster prominence are calculated. Alternatively, the proposed method is implemented with mean and standard deviation of pixel values as the features, instead of Harlick features.

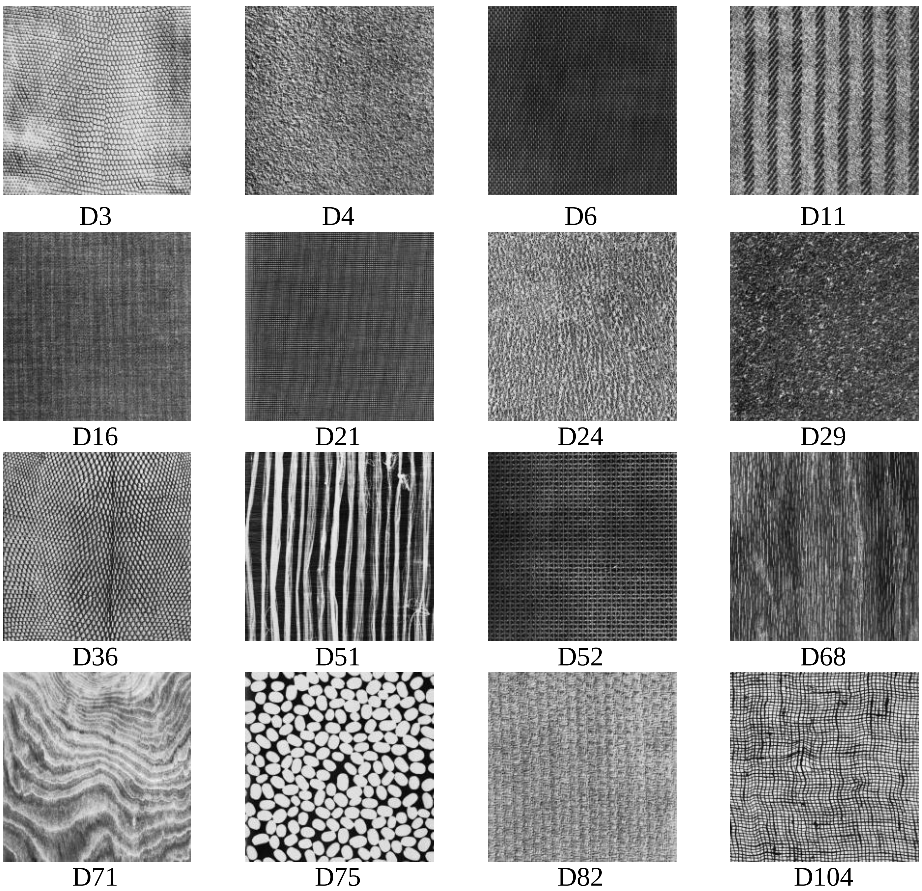

Fig. 4 Texture images from Brodatz album

The LDBP approach is used to extract the rotational invariant coefficients of the image (which produces 62*62=3844 features). The operator labels the pixels of an image by thresholding a 3x3 neighborhood of each pixel with center value and considering the results as binary number. Further 3844 labels computed over a region are used as a texture descriptor. The derived numbers (called Local directional binary patterns or LDBP codes) codify local primitives including different types of curved edges, spots, flat areas etc. The feature set so obtained from NSCT co-occurrence features and LDBP has 3949 features for proposed method with Harlick features and 3874 features in case of moment features, mean and standard deviation. This feature set suffers from high dimensionality, which creates problems in constructing efficient data structure for classification. Hence PCA-LDA is applied for dimensionality reduction and class seperability enhancement. The k-NN classifier is applied in order to investigate the most representative set. The implementation of the NSCT is based on pyramidal filtering and directional filtering. Extensive experiments are carried out using different Laplacian pyramidal (LP) filters for each of the different directional filters (DFB). Four categories of pyramid filters, namely, '9-7', 'maxflat', 'pyr' and 'pyrexc' are considered, while fifteen categories of directional filters, namely, 'haar', 'dmaxflat4', ' dmaxflat5', 'dmaxflat6', 'dmaxflat7', 'qmf2', 'qmf', 'lax', 'pkva', 'ko', 'sinc', 'sk', 'vk', 'cd', 'dvmlp' filters are considered. We have investigated all pairs of pyramidal filter and directional filter for different levels. For each filter pair, the decomposition level is carried upto level 4. The Table I shows the optimal average classification results yielded by the optimal pair of filters at the four levels.

TABLE I
OPTIMAL CLASSIFICATION ACCURACY FOR DIFFERENT LEVELS

Pyramidal Decomposition Level	**Optimal Pair of Filters**	**Average Classification Accuracy**
Level 1	ko, pyrexc	69.125%
Level 2	dmaxflat7, 9-7	94.531%
Level 3	dmaxflat6, pyrexc	**98.438**%
Level 4	sk, pyrexc	94.531%

It is observed that level 3 pyramidal decomposition gives the better classification accuracy for the combination of directional filter 'dmaxflat6' and pyramid filter 'pyrexc'. The spatial details are well captured in decomposition level 3. The diamond maxflat filter uses three stage ladder structure. The Table II shows the average classification accuracy for the 16 texture categories of Brodatz [22] for level 3 for all possible combinations of filters. It is observed that the proposed method with directional filter 'dmaxflat6' and pyramid filter 'pyrexc' shows optimal average classification accuracy of 98.4375% with level 3 decomposition and 15 directional subbands.

TABLE II
AVERAGE CLASSIFICATION ACCURACY (%) OF PROPOSED METHOD USING DIFFERENT DIRECTIONAL FILTERS AND PYRAMIDAL FILTERS OF NSCT FOR 16 TEXTURE CATEGORIES OF BRODATZ [22]

Sl. No.	**Directional Filters for NSCT**	**Average Classification Accuracy (%)**			
		Pyramidal Filters of NSCT			
		pyr	**maxflat**	**9-7**	**pyrexc**
1	haar	96.0938	92.9688	96.0938	93.7500
2	dmaxflat4	96.8750	94.5313	94.5313	95.3125
3	dmaxflat5	97.6563	95.3125	96.0938	96.8750
4	dmaxflat6	97.6563	95.3125	96.0938	**98.4375**
5	dmaxflat7	96.0938	94.5313	96.8750	96.8750
6	qmf2	96.0938	92.9688	96.8750	88.2813
7	qmf	92.9688	94.5313	93.7500	93.7500
8	lax	94.5313	94.5313	87.5000	95.3125
9	pkva	94.5313	90.6250	94.5313	93.7500
10	ko	91.4063	87.5000	96.0938	95.3125
11	sinc	90.6250	91.4063	92.9688	92.9688
12	sk	95.3125	93.7500	93.7500	96.0938
13	vk	93.7500	86.7188	92.1875	94.5313
14	cd	88.2813	93.7500	96.0938	89.0625
15	dvmlp	92.1875	90.6250	90.6250	94.5313

The Table III shows the comparison of classification accuracies for each texture class obtained by the proposed method and other methods in the literature. It is noticed that the proposed method based on Harlick features offers good classification performance. The proposed method with 2-D pyramidal filter 'pyrexc' and directional 2-D filter 'dmaxflat6' for NSCT using Harlick features yields 98.4375% mean success rate. The experimental results indicate that the proposed method is effective in terms of classification accuracy and reduced feature set.

TABLE III

COMPARISON OF CLASSIFICATION ACCURACIES (%) FOR 16 TEXTURE CATEGORIES

Sl. No.	Image Name (Brodatz)	Hiremath and Shivshankar [9] (105 features)	Zhao et al. [19] with k-NN (288 features)	Proposed Method with μ and σ features (12 features)	Proposed Method with Harlick features (15 features)
1	D104	93.47	100	100	100
2	D11	84.38	25	87.5	100
3	D16	93.48	100	100	100
4	D21	100	100	100	100
5	D24	79.63	50	87.5	100
6	D29	84.92	37.5	62.5	100
7	D3	86.9	75	100	100
8	D36	72.34	75	100	87.5
9	D4	76.19	100	25	100
10	D51	59.81	50	100	100
11	D52	59.57	75	100	100
12	D6	91.67	87.5	100	100
13	D68	82.13	100	100	100
14	D71	100	100	62.5	100
15	D75	77.81	100	100	100
16	D82	56.23	87.5	87.5	87.5
Mean success rate		81.1581	78.9063	88.28125	98.4375

VII. CONCLUSION

In this paper, a novel texture classification method is proposed. Nonsubsampled contourlet transform has the translation invariability, which improves classification. Local directional binary pattern has rotational invariance. The method uses co-occurrence features of three level NSCT decomposition and LDBP weights to represent the texture characteristics. The high dimensionality of feature set so obtained is reduced by PCA and class discriminality is enhanced using LDA. The features obtained from LDA are the representatives of each class. The classification performance is tested on sixteen Brodatz textures. The k-NN classifier with k=3 is used to classify images. Experimental results exhibit the effectiveness of proposed method in terms of classification accuracy and minimal feature set.

REFERENCES

[1] R. M. Harlick, K. Shanmugam and I. dinsein, “Texture features for image classification,” *IEEE Trans. on System, Man and Cybernetics*, no. 3, pp. 610-621, 1973.

[2] H. Tamura, S. Mori and Y. Yamawaki, “Textural features corresponding to visual perception”, *IEEE Trans. on Systems, Man and Cybernetics*, no. 8, pp. 460-473, 1978.

[3] J. R. Smith and S. F. Chang, “Visually searching the web for content,” IEEE Multimedia magazine vol. 4 no. 3, pp. 12-20, 1997, (Columbia U. CU/CTR Tech. Rep. 459-96-25).

[4] J. R. Smith and S. F. Chang, “Transform features for texture classification and discrimination in large image databases,” in *Proc. IEEE Int. Conf. on Image Proc.*, 1994.

[5] K. S. Thyagrajan, T. Nguyen, C. Person, “A maximum likelihood approach to texture classification using wavelet transform,” in *Proc. IEEE Int. Conf. on Image Proc.*,1994.

[6] T. Ojala, M. Pietikainen and T. Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with Local Binary Pattern,” *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971-987, 2002.

[7] A. Laine and J. Fan, “Texture classification by wavelet packet signatures,” *IEEE Trans. on Pattern Analysis and Machine intelligence*, vol. 15, no. 11, pp. 1186-1191, 1993.

[8] S. Arivazhagan and L. Ganeshan, “Texture classification using wavelet transform,” *Pattern recognition letter 24*, pp. 1513-1521, 2003.

[9] P.S. Hiremath and S. Shivshankar, “Texture classification using wavelet packet decomposition,” *ICGST Int. journal on Graphics, Vision and image processing*, vol. 6, no. 2, pp. 77-80, Sept. 2006.

[10] M. N. Do. and M. Vetterli, “Contourlet: A new directional multiresolution image representation,” in *Proc. of Conf. record of the thiry-sixth Asilomar Conf. on Signals, System and Computers*, pp. 497-501, 2002.

[11] M. N. Do. and M. Vetterli, “The contourlet transform: an efficient directional multiresolution image representation,” *IEEE Trans. on image Processing*, vol. 14 no. 12, pp. 2091-2106, Dec. 2005.

[12] Z. Liu, “Minimum distance texture classification of SAR image in contourlet domain,” *Int. Conf. on Computer*

Science and Software Engineering, pp. 834-837, 2008 .
[13] P. Tsakanikas and E. S. Manolakos, "Improving 2-DE gel image denoising using contourlets," *Proteomics*, vol. 9, no. 15, pp. 3877-3888, Aug. 2009.
[14] D. A. Karras, S. A. Karkanis and B. G. Mertzois, "Image compression using the Wavelet transform on textural regions of interest," *24th Euromicro conf.*, vol. 2, pp. 633-639, Aug. 1998.
[15] A. L. Cunha, J. P. Zhou and M.N. Do, "The nonsubsampled contourlet transform: theory, design and applications," *IEEE Trans. on Image Processing*, vol.15, no. 10, pp. 3089-3101, 2006.
[16] M. A. L. Vijilious and V. S. Bharathi, "Texture classification using reduced set of nonsubsampled contourlet transform features," *Recent Trends In Information Technology (ICRTIT), 2012, Int. Conf.*, pp. 77 - 80 , April 2012.
[17] Liu Mingxia, Hou Yingkun, Guo Xiaochun, and Yang Deyun , "Texture Classification Using Nonsubsampled Contourlet Transform and LS-SVM", *Image and Signal Processing, 2009 (CISP 09), 2nd Int. Congress*, pp. 1–5, Oct. 2009.
[18] Wang Hai feng, Li Zhuang , Ren Hong and Zhao Peng , "Texture image segmentation algorithm based on nonsubsampled contourlet transform and SVM," *Control Conference (CCC)*, pp. 2712–2716, July 2010.
[19] Zhengli Zhu, Chunxia Zhao and Yingkun Hou, "Texture image classification based on nonsubsampled contourlet transform and local binary patterns," *Int. journal of digital content technology and its applications*, vol. 4, no. 9, pp. 186-193, 2010.
[20] Arif Ghafoor, "Multimedia database management system", *ACM Comput. Surv.*, vol. 27, no. 4, pp. 593-598, 1995.
[21] R. O. Duda, P.E. Hart and Stork, *Pattern classification*, Wiley publication, New York, 2001.
[22] P. Brodatz, "Textures: A photographic album of artists and designers," Dover publication, New York, 1966.
[23] J. Zhou, A. L. Cunha and M. N. Do, "Nonsubsampled contourlet transform: construction and application in enhancement," *Proc. Int. Conf. on Image Processing (ICIP)*, vol. 1, pp. 469–472, Sept. 2005.
[24] B. Bin Yang, Shutao Li and Fengmei Sun, "Image fusion using nonsubsampled contourlet transform," *Proc. of the 4th Int. Conf. on Image and Graphics (ICIG)*, pp. 719–724, Aug. 2007.
[25] R.H. Bamberger and M.J.T. Smith, "A filter bank for the directional decomposition of images: theory and design," *IEEE Trans. on Signal Processing*, vol. 40 no. 4, pp. 882-893, April 1992.

