Nonsubsampled Contourlet Transform and Local Directional Binary Patterns for Texture Image Classification Using Support Vector Machine

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Abstract

Texture is a surface characteristic property of an object. Texture analysis is an important field of investigation that has received a great deal of interest from computer vision community. In this paper, a translation and rotation invariant texture classification method based on support vector machine is proposed. Texture features are extracted using nonsubsampled contourlet transform and local directional binary patterns. Co-occurrence features are extracted for three level nonsubsampled contourlet 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). Support vector machine is used as classifier. The classification performance of the proposed method is tested on a set of sixteen Brodatz textures. Experimental results indicate that the proposed approach yields higher classification accuracy.

Keywords-NSCT, Principal component analysis, LDBP, Linear discriminant analysis, SVM, Texture classification.

1. Introduction

Texture is a inherent property of most of natural images. It contains information about the structural arrangement of surface and their relationship to the surrounding environment. Texture characteristics play a very important role in texture analysis. Texture classification is one of the fundamental problem in computer vision and has a wide variety of potential applications. Weszka et al. [1] compared the classification performance of Fourier power spectrum, second order gray level co-occurrence matrix (GLCM), and first order statistics of gray level differences for terrain samples. It is observed that Fourier methods performed poorly. Harlick et al. [2] suggested the use of GLCM texture features to analyze remotely sensed images. Wan et al. [3] presented comparative study of four texture analysis methods namely gray level run length method, co-occurrence matrix method, histogram method and autocorrelation method, wherein co-occurrence method is found to be superior. Wavelet transform [4, 5] provides a multi resolution approach for the problem. Smith and Chang [6] used mean and variance extracted from wavelet subband coefficients, as the texture representation.

Classification methods can be divided into categories namely: (i) parametric, (ii) non-parametric, (iii) stochastic methods and (iv) non-metric methods [7]. Classification task involves classifying images based on the feature vectors provided by the feature extraction methods. If there is no prior parameterized knowledge about the probability structure, then classification is based on non-parametric techniques. The classification so performed is based on information provided by training samples alone. These techniques include fuzzy classification, neural network approach, etc. Engin Avci [8] used multilayer perceptron neural network classifier to classify selected texture images. Turkoglu and Avci [9] presented a comparison of wavelet support vector machine and wavelet-adaptive network based fuzzy inference system approaches for texture image classification. Both the methods are used for classification of the 22 texture images. Schaefer et al. [10] used fuzzy classification for thermograph based breast cancer analysis using statistical features. Mukane et al. carried out the scale invariant, size invariant and rotation invariant [11, 12, 13] classification with wavelet and co-occurrence matrix based features using fuzzy logic classifier. Laine and Fan [14] implemented standard wavelet packet energy signature for texture classification. Pun and Lee [15] used Log-polar wavelet signature with Mahalanobis classifier for scale and rotation invariant texture classification. Cui et al. [16] performed experiment for rotation invariant texture classification based on radon transform and multi-scale analysis with Mahalanobis classifier. Hiremath and Shivashankar [17] proposed wavelet based co-occurrence features for texture classification with k-NN classifier. Arivazhagan et al. [18] used Gabor features for rotation invariant texture classification with minimum distance classifier. The wavelet transform offers a multiscale and time-frequency-localized presentation. However, the 2-D separable wavelet basis has limited directional information, which can not describe the multi direction of various textures. This gave rise to several successful joint statistical models such as steerable pyramid, brushlets, curvelet transform and contourlet transform. In particular, the contourlet transform proves to be optimal in dealing with images having smooth contours. Due to upsamplers and downsamplers present in the Laplacian pyramid and directional filter bank (DFB), the contourlet transform is not shift invariant [19]. Cunha et al. [20] developed the nonsubsampled contourlet transform (NSCT), which is a shift-invariant, multiscale and multidirection expansion. The NSCT has proven to be very efficient in image processing applications such as image denoising and image enhancement. Zhao et al. [21] have presented an approach of texture image classification based on nonsubsampled contourlet transform, local binary patterns and support vector machine for classification. In [22], the approach which mainly consists of two learning steps: first extracting the features using three level NSCT and second is extraction of features using local directional binary patterns (LDBP), followed by classification using k-NN classifier is proposed. In general, optimal parameters can vary depending on the intrinsic scale and complexity of the texture patterns.

This paper focuses on the problem of texture classification. In [22] a texture image classification problem using k-NN classifier is investigated. The aim of this paper is to improve the classification accuracy using support vector machine as classifier. The translation and rotation invariant texture classification method is proposed to extract the textural features. NSCT has translation invariability, while LDBP has rotation invariance. To reduce the dimensionality of feature set and enhance class discrimination, principal component analysis (PCA) and linear discriminant analysis (LDA) is implemented. The classification is performed using support vector machine. The experimentation is done using Brodatz [23] images. The experimental results show that the proposed method exhibits optimal performance.

2. Nonsubsampled contourlet transform

In the nonsubsampled contourlet transform (NSCT) [20] method, the main focus is to avoid the frequency aliasing problem, enhance 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 as shown in the Figure 1. Initially, the nonsubsampled pyramid split the input image into lowpass and highpass subband. Then a nonsubsampled DFB is applied to decompose the highpass subband into several directional subbands by increasing the number of directions with frequency. This step is repeatedly iterated on the lowpass subband. In NSCT, the multiresolution decomposition is done by shift invariant filter banks which satisfy Bezout identical equation. The lowpass subband has no frequency aliasing effect because of no downsampling in the pyramidal decomposition level. Hence, the bandwidth of lowpass filter is larger than $\pi/2$. The NSCT has better frequency characteristics than the CT. The perfect reconstruction condition is given in the Eq. (1). The nonsubsampled pyramid and nonsubsampled DFB are depicted in the Figure 1.(a) and Figure 1.(b), respectively.

$$H_0(z)G_0(z) + H_1(z)G_1(z) = 1 \quad (1)$$

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

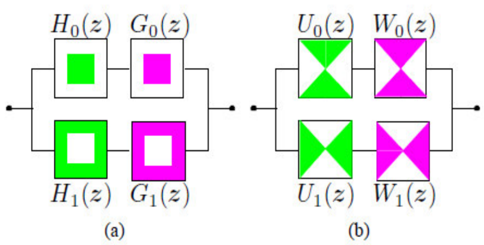

Figure 1. (a) nonsubsampled pyramid, (b) nonsubsampled DFB.

The Figure 2. shows the two-level decomposition of NSCT, which provides multiscale, multidirection, and shift invariant image decomposition. The frequency division of a nonsubsampled pyramid is shown in the Figure 2.(a) and of nonsubsampled DFB is shown in the Figure 2.(b). The NSCT is the non separable twochannel filter bank composed of basis function oriented at various directions in multiple scales, with different aspect ratios. With this rich set of basis functions, it captures smooth contours that are the dominant features in textures effectively. Since the NSCT has desirable properties of shift invariance, it is used to extract features from the texture images.

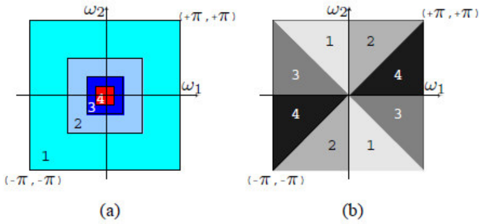

Figure 2. Frequency divisions of: (a) a nonsubsampled pyramid, (b) a nonsubsampled DFB.

The input texture image is decomposed into subbands by the nonsubsampled contourlet transform at four different resolution levels as shown in the Figure 3. The block diagram and resulting frequency division of NSCT is shown in the Figure 3.(a) and Figure 3.(b). At each resolution level, it is decomposed into 2^n subbands, where n = 0, 1, 2, 3, 4, ... and is the order of the directional filter. As the transform is nonsubsampled, each resolution level corresponds to the actual size of the input block, i.e. 64x64. Since the features generated are in larger number, the procedure of involving the entire coefficients in classification is more time consuming.

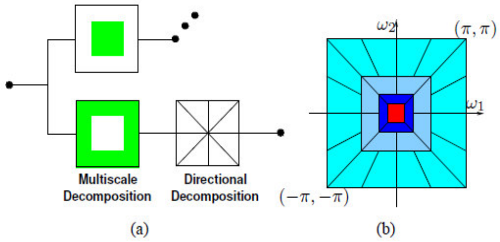

Figure 3. The NSCT: (a) block diagram, (b) resulting frequency division.

3. Local directional binary patterns

A method based on local directional binary patterns (LDBP) is a theoretically and computationally simple approach which is robust in terms of gray scale variations. It is shown to discriminate a large range of rotated textures efficiently. A gray-scale and rotation invariant texture operator based on LDBP is described as follows: Starting from the joint distribution of gray values of a circularly symmetric neighbour set of pixels in a local neighbourhood, an operator is derived which is, by definition, invariant against any monotonic transformation of the gray scale. Rotation invariance is achieved by recognizing that this gray-scale invariant operator incorporates a fixed set of rotation invariant patterns. The main contribution lies in recognizing that certain local binary texture patterns are fundamental properties of local image texture. There are a limited number of transitions or discontinuities in the circular representation of the pattern. The most frequent binary patterns correspond to primitive micro features, such as edges, corners and spots; hence, they can be regarded as feature detectors that are triggered by the best matching pattern. The proposed texture operator allows for detecting local directional binary patterns at circular neighbourhoods of any quantization of the angular space and at any spatial resolution is shown in the Figure 4.

The derivation of our gray scale and rotation invariant texture operator is done by defining texture T in a local neighbourhood of a monochrome texture image as the joint distribution of the gray levels of p (p>1) image pixels is represented by the Eq. (2):

$$T = t(f_c, f_0, \ldots, f_{p-1}), \qquad (2)$$

where gray value f_c corresponds to the gray value of the center pixel of the local neighbourhood and $f_p(p = 0, \ldots, p-1)$ correspond to the gray values of p equally spaced pixels on a circle of radius R (R>0) that form a circularly symmetric neighbour set.

The first step toward gray-scale invariance is to subtract, without losing information, the gray value of the center pixel (f_c) from the gray values of the circularly symmetric neighbourhood and to assume that difference $f_p - f_c$ is independent of f_c, which yields the Eq. (3):

$$T = t(f_c)\; t(f_0 - f_c, f_1 - f_c, \ldots\ldots, f_7 - f_c) \qquad (3)$$

In practice, an exact independence is not warranted; hence, the above distribution is only an approximation of the joint distribution. However, it is tolerable to accept the possible small loss in information as it achieves invariance with respect to shifts in gray scale. The distribution $t(f_c)$ in the Eq. (3) describes the overall luminance of the image, which is unrelated to local image texture and consequently, does not provide useful information for texture analysis. Hence, much of

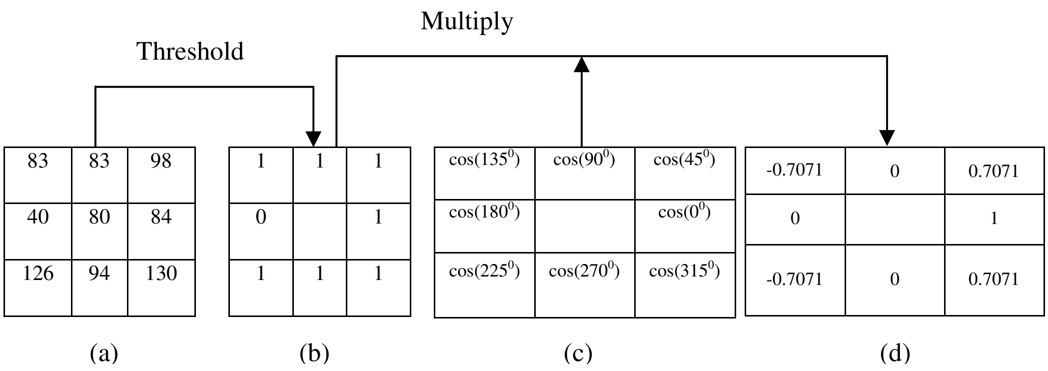

Figure 4. Transformation of neighborhood pixels to calculate central pixel weight in LDBP. (a) A sample neighborhood, (b) Resulting binary thresholded result, (c) LDBP mask, (d) Resultant weights after multiplying corresponding elements of (b) and (c)

the information in the original joint gray level distribution is as shown in the Eq. (4):

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

This is a highly discriminative texture operator. It records the occurrences of various patterns in the neighbourhood of each pixel in a P-dimensional histogram. For constant regions, the differences are zero in all directions. On a slowly sloped edge, the operator records the highest difference in the gradient direction and zero values along the edge. For a spot, the differences are high in all directions. Signed differences $f_p - f_c$ are not affected by changes in mean luminance; hence, the joint difference distribution is invariant against gray-scale shifts. We achieve invariance with respect to the scaling of the gray scale by considering just the signs of the differences instead of their exact values as in the Eq. (5):

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

where

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

By assigning a cosine factor $\cos(\theta)$ for each sign $v\left(f_p - f_c\right)$, we transform the Eq. (5) into a unique LDBP number that characterizes the spatial structure of the local image texture as given in the Eq. (7):

$$f_b\left(x_c, x_c\right) = \sum_{k=0}^{7} v\left(f_k - f_c\right)\cos(k * 45) \qquad (7)$$

A local neighborhood is thresholded at the gray value of the center pixel into a binary pattern. The LDBP operator is by definition invariant against any monotonic transformation of the gray scale, i.e., as long as the order of the gray values in the image stays the same, the output of the LDBP operator remains constant.

4. PCA-LDA

In practice, dimensionality reduction is important in handling high dimensional data since it mitigates the curse of dimensionality and other undesired properties of high dimensional spaces. The most widely used method is principal component analysis (PCA). The class seperability is guaranteed by the linear discriminant analysis (LDA). 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 Eqs. (8) and (9):

- Within class scatter matrix:

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

where y_i^j is ith 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.

- Between class scatter matrix:

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

where μ represents mean of all classes, y_i^j is ith 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. The objective is to maximize the between class measure while minimizing the within class measure.

5. Support vector machines

The support vector machine (SVM) [24] is designed to work with only two classes by determining the hyperplane to divide two classes. The samples closest to the margin that were selected to determine the hyperplane is known as support vectors. Basic principle of support vector machines is that, first, samples of input space can be converted into linear samples of a high dimensional space by nonlinear transform, optimal linear classification surface can be done by calculation in high dimension space [25]. The nonlinear transform can be realized by the appropriate inner product function.

Different kernel functions can get different methods of support vector machines. At present, there are three main kinds of kernel function as follows:

1) kernel function using polynomial is defined by the Eq. (10):

$$K(x, x_i) = [(x.x_i) + 1]^q \tag{10}$$

SVM is a polynomial classifier with q order.

2) kernel function using the Gaussian radial basis function is represented as in the Eq. (11):

$$K(x, x_i) = \exp\left\{-\frac{|x - x_i|^2}{\sigma^2}\right\} \tag{11}$$

SVM is a kind of radial basis function classifier.

3) kernel function using Sigmoid function is given by the Eq. (12):

$$K(x, x_i) = \tanh(v(x, x_i) + c) \tag{12}$$

Each kernel function has parameters whose value has to be changed and tuned according to the data set. Polynomial kernel function produces a polynomial separating hyperplane whereas Gaussian kernel function produces a Gaussian separating hyperplane. So, depending on the level of non separability of data set, the kernel function is chosen.

6. 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 Figure 5. shows the block diagram of the proposed method. In the experimentation, sixteen texture images [22] from the Brodatz texture [23] are used for classification. Each image represents one texture class. Texture images are sampled to 256x256 size. Each texture image is divided into 16 equal sized nonoverlapping blocks of size 64x64, out of which 8 randomly chosen blocks are used as training samples and remaining blocks are used as test samples for each texture class.

6.1. Texture training module

Feature database is created using nonsubsampled contourlet transform upto third level of decomposition. We get fifteen subbands for level 3 of decomposition on NSCT. The Harlick features namely, contrast, energy, entropy, homogeneity, maximum probability, cluster shade and cluster prominence of each subband coefficients are calculated to obtain eigenvector F1. The LDBP weights of each block are calculated, which are used as eigenvector F2, containing 3844 features (=62*62, since image edges are excluded). The steps of the proposed training module are given in the Algorithm 1.

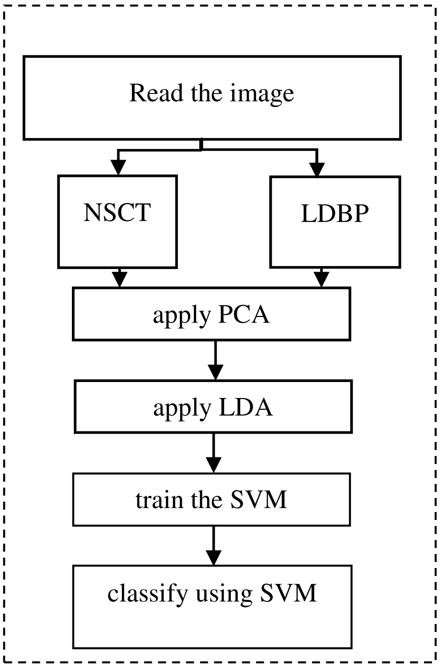

Figure 5. Block diagram of the proposed method

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 training SVM.
Step 9: SVM is trained using polynomial kernel of order 9 using the TFLDA to obtain the SVM structure TFSVM, which is to be used for texture classification.
Step 10: Stop

In step 9, the SVM with polynomial kernel of order 9 is used, since it is observed to yield optimal results as compared to Gaussian radial basis kernel and Sigmoid kernel function, which is indicated by the experimental results.

6.2. Texture classification module

The support vector machine (SVM) [24] classifier is used to realize the automatic texture classification, with polynomial function as kernel function as given by the Eq. (10). The steps of 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 Itest 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 SVM classifier (with polynomial kernel of order 9) to classify the test image I_{test} as belonging to class m.
Step 9: Stop.

7. Experimental results and discussion

7.1. Image database

For the experimentation, sixteen different texture classes from Brodatz album [23] are used which are shown in the Figure 6. Each 256x256 images of texture classes are divided into 16 non overlapping block of pixel 64x64. Thus, there are 256 blocks in the experiment database. The 50% of blocks of each type image in experiment database are used as training samples, so there are 128 blocks which are used as training samples. Remaining 50% of blocks of each type image in experiment database are used as test samples, so remaining 128 blocks are used as test samples. In order to estimate the performance for classification, the training and testing sets should be independent and randomly divided. The good features should not be wasted with poor classifier, so we use SVM classifier to perform texture classification. The inputs to the systems are the digitized images from one of the texture classes. When each type sub-images of training samples are trained, at this time, this type sub-images are positive, other type sub-images of training samples are negative.

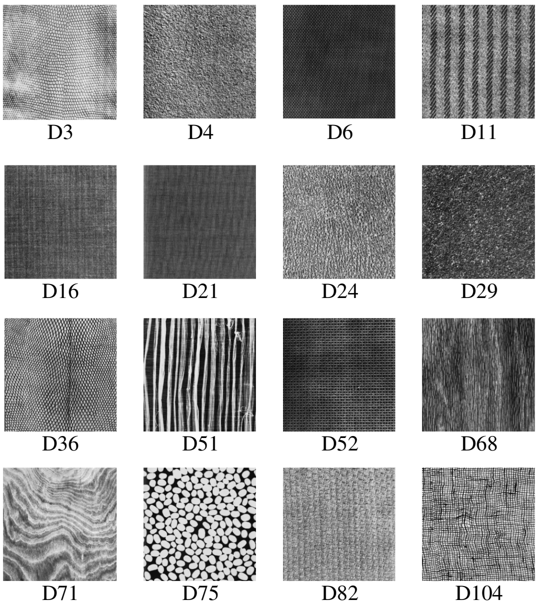

Figure 6. Texture images from Brodatz album

7.2. 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 texture image is decomposed into subbands upto three levels, at each resolution, it is decomposed into 2^n subbands. Thus the input image is decomposed into fifteen subbands. As the transform is nonsubsampled, each subband corresponds to the actual size of texture image. 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 features namely, contrast, energy, entropy, homogeneity, maximum probability, cluster shade and cluster prominence are calculated for each subband of the decomposed image.

The implementation of the NSCT is based on pyramidal filtering and directional filtering. 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 level 3. The results of extensive experimental activity are summarised in the Table 1. The proposed method improves average classification accuracy to 100% on the image database. The proposed method achieves promising results in texture classification as compared to classification technique discussed in [22]. The Table 1. shows the average classification accuracy for the 16 texture categories of Brodatz [23] for level 3 decomposition of NSCT for all possible combinations of filters.

The LDBP coefficients are used to represent the different textures. LDBP coefficients do not require additional comlex computation for feature extraction. An image in LDBP transformation is represented as sum of sinusoids of changing magnitudes and frequencies. 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. To reduce the redundant information (i.e. the information contained in some highly correlated features) and to improve the class seperability, two statistical analysis techniques called PCA and LDA are used in the experimentation. Thus, the vast numbers of features are reduced in greater dimension and used for training the support vector machine.

The support vector machine is employed to perform texture classification using the features extracted by the proposed method. The support vector machine is a theoretically superior learning methodology with increased classification accuracy for high dimensional datasets and has been found competitive with the best machine learning algorithm. The performance of SVM classifier depends on the type of kernel function and SVM parameters. SVMs have been tested and evaluated only as pixel based image classifier. The SVM method was designed to be applied only for two class problems [23-24]. For applying SVM to multiclass classification the basic idea is to reduce the multiclass to set of binary problems so that the SVM approach can be used. There is no fixed rule in the choice of kernel function. But it is seen that polynomial kernel function works generally well with non-separable data sets. By increasing the degree of the function, one can get zero misclassification for the training set at least. In the proposed study the polynomial kernel of order 9 is implemented.

Table 1. Average classification accuracy (%) of proposed method using different directional filters and pyramidal filters of NSCT (level 3) 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	93.750	85.156	100	100
2	dmaxflat4	90.625	100	88.281	100
3	dmaxflat5	82.813	100	88.281	93.750
4	dmaxflat6	100	100	83.594	100
5	dmaxflat7	87.500	100	88.281	83.594
6	qmf2	96.094	70.313	100	100
7	qmf	100	93.750	94.531	94.531
8	lax	100	96.094	93.750	64.063
9	pkva	87.500	93.750	94.531	92.969
10	ko	93.750	96.094	100	100
11	sinc	79.688	94.531	95.313	82.813
12	sk	77.344	100	76.563	100
13	vk	100	100	88.281	100
14	cd	86.719	100	93.750	93.750
15	dvmlp	100	100	100	83.594

The Table 2. shows the pairs of 2-D directional filter and pyramidal filter used in the proposed method, which yielded optimal result (100%).

Table 2. The different pairs of 2-D directional filter and pyramidal filter, which yield optimal result (100%).

Sl. No.	Pair of 2-D directional filter and pyramidal filter.	Time in sec.	
		Training	Testing
1	haar, 9-7	258.5018	10.4278
2	haar, pyrexc	261.8971	10.1643
3	dmaxxflat4, maxflat	301.3827	12.7742
4	dmaxxflat4, pyrexc	303.0670	12.9953
5	dmaxflat5, maxflat	329.2040	15.405
6	dmaxflat6, pyr	350.5524	16.3876
7	dmaxflat6, maxflat	351.6857	15.8956
8	dmaxflat6, pyrexc	352.2076	15.415
9	dmaxflat7, maxflat	384.4168	17.9869
10	qmf2, 9-7	262.6677	10.6049
11	qmf2, pyrexc	261.9525	10.3589
12	qmf, pyr	265.6508	10.5738
13	lax, pyr	282.8375	11.6374
14	ko, 9-7	259.1459	10.2003
15	ko, pyrexc	259.8482	10.2113
16	sk, maxflat	259.9656	10.8193
17	sk, pyrexc	261.0526	10.4756
18	vk, pyr	259.9656	10.2229
19	vk, maxflat	261.0526	10.3571
20	vk, pyrexc	260.7513	10.1785
21	cd, maxflat	267.4015	10.8224
22	dvmlp, pyr	267.4773	10.7117
23	dvmlp, maxflat	267.2677	10.7314
24	dvmlp, 9-7	266.229	10.6799

The Table 3. shows the comparison of classification accuracies for each texture class obtained by the proposed method using haar and 9-7 as optimal pair of 2-D directional filter and pyramidal filter and other methods in the literature which are implemented on the experimental database.

Table 3. Comparison of classification accuracies (%) by different methods for 16 texture categories

Sl. No.	Image Name (Brodatz)	Hiremath and Shivashankar [17] with k-NN (105 features)	Zhao et al. [21] with k-NN (288 features)	Hiremath and Rohini [22] with k-NN (15 features)	Zhao et al. [21] with SVM (288 features)	Proposed Method with SVM (15 features)
1	D104	93.47	100	100	100	100
2	D11	84.38	25	100	100	100
3	D16	93.48	100	100	100	100
4	D21	100	100	100	100	100
5	D24	79.63	50	100	100	100
6	D29	84.92	37.5	100	100	100
7	D3	86.9	75	100	100	100
8	D36	72.34	75	87.5	87.5	100
9	D4	76.19	100	100	100	100
10	D51	59.81	50	100	100	100
11	D52	59.57	75	100	100	100
12	D6	91.67	87.5	100	100	100
13	D68	82.13	100	100	100	100
14	D71	100	100	100	100	100
15	D75	77.81	100	100	100	100
16	D82	56.23	87.5	87.5	100	100
Mean classification rate		81.158	78.906	98.437	99.210	100.0

The systematic comparison of the experimental results demonstrate that the proposed algorithm yields better results. The SVM classifier helps to improve the classification accuracy. The proposed system performs the better, among other approaches in the literature, yielding an accuracy of 100%.

8. Conclusion

In this paper, a novel algorithm for texture image classification using support vector machine is proposed. Features are extracted using nonsubsampled contourlet transform and local directional binary patterns. To decrease the dimensionality of feature vector and to enhance the discriminality of classes, PCA, LDA techniques are used. Support vector machine is used to classify textured images. The classification performance is tested on sixteen Brodatz textures. The SVM classifier is found to give high classification accuracy and a smaller misclassification rate as compared to the other classifier techniques. Experimental results show that the proposed approach enhances average precision of texture image classification.

9. References

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