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Non Subsampled Shearlet Transform Based Texture Classification Using Sub Band Energy

KEYWORDS: Texture, image classification, non subsampled shearlet transform, energy, nearest neighbor classifier

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ABSTRACT *In this paper, an efficient approach for the classification of texture images based on non subsampled shearlet transform (NSST) is proposed. The classification of texture is achieved by extracting sub band energy from the shearlet decomposed image. First, the texture image is decomposed by NSST at various decomposition levels with multi-directions. Then the proposed sub band energy is extracted from each sub-band of the decomposed image. Sub band 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 method. The performance is compared with state of art techniques involving wavelet transform, gabor transform and statistical features. The results show that the NSST based classification provides better classification accuracy.*

1. Introduction
Texture classification is the most important 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.

2. Related Works
Gaussian Markov Random Field (GMRF) model is used on linear wavelets for the classification of textures by (B.V. Ramana Reddy et el, 2010). 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 by (Liran Shen, Qingbo Yin, 2009) 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 (S. Pharsooki et al, 2011). The dictionary of textons is learned by applying sparse representation to image patches in the training dataset.

A new approach to extract global image features for the purpose of texture classification using dominant neighborhood structure is proposed in(Abdulkadir Sengur,2009).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 (P.S. Hiremath, S.Shivashankar, 2006) 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 (Jean Francois Aujol et al,2003).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. An efficient one-nearest-neighbor classifier of texture via the contrast of local energy histograms of all the wavelet subbands between an input texture patch and each sample texture patch in a given training set is described.

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

3. Non Subsampled Shearlet Transform
The proposed texture classification approach is based on new multi-scale directional representations called the shearlet transform introduced by the authors in (Glenn Easley. et.al., 2007). An image consists of a finite sequence of values,

$$\{x[n_1, n_2]_{n_1,n_2=0}^{N-1,N-1}\}$$

where $N \in$ N. Identifying the domain with the finite group Z_N^2, the inner product of image $Z_N^2 \rightarrow$ C is defined as

$$(x, y) = \sum_{u=0}^{N-1}\sum_{v=0}^{N-1} x(u,v)\overline{y(u,v)} \qquad (1)$$

Thus the discrete analog of $L^2(R^2)$ is $l^2 Z_N^2$. Given an image $f \in l^2(Z_N^2)$, let $\hat{f}[k_1,k_2]$ denote its 2D Discrete Fourier Transform (DFT):

$$\hat{f}[k_1,k_2] = \frac{1}{N}\sum_{n_1,n_2=0}^{N-1} f[n_1,n_2]e^{-2\Pi i(\frac{n_1}{N}k_1+\frac{n_1}{N}k_2)} \qquad (2)$$

The brackets in the equations $[\cdot,\cdot]$ denote arrays of indices, and parentheses $(\cdot,\cdot)$ denote function evaluations. Then the

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$$\hat{f}[k_1,k_2] = \hat{f}(k_1,k_2)$$

interpretation of the numbers $\hat{f}[k_1,k_2]$ as samples is given by the following equation from the trigonometric polynomial.

$$\hat{f}(\xi_1,\xi_2) = \sum_{n_1,n_2=0}^{N-1} f[n_1,n_2] e^{-2\prod i(\frac{n_1}{N}\xi_1+\frac{n_1}{N}\xi_2)} \tag{3}$$

First, to compute

$$\hat{f}(\xi_1,\xi_2)\overline{V(2^{-2j}\xi_1,2^{-2j}\xi_2)} \tag{4}$$

In the discrete domain, at the resolution level j , the Laplacian pyramid algorithm is implemented in the time domain. This will accomplish the multi scale partition by decomposing

$$f_a^{j-1}[n_1,n_2],\ 0 \le n_1,n_2 < N_j - 1'$$

into a low pass filtered image $f_a^j[n_1,n_2]$, a quarter of the size of $f_a^{j-1}[n_1,n_2]$, and a high pass filtered image $f_d^{j-1}[n_1,n_2]$.

Observe that the matrix $f_a^{j-1}[n_1,n_2]$ has size $N_j * N_j$,where $N_j = 2^{-2j} N$ and $f_a^0[n_1,n_2] = f[n_1,n_2]$ has size $N * N$. In particular,

$$\hat{f}_d^{\,j}(\xi_1,\xi_2) = \hat{f}(\xi_1,\xi_2)\overline{V(2^{-2j}\xi_1,2^{-2j}\xi_2)} \tag{5}$$

Thus, $f_d^j[n_1,n_2]$ are the discrete samples of a function $f_d^j[x_1,x_2]$, whose Fourier transform is $\hat{f}_d^{\,j}(\xi_1,\xi_2)$ .In order to obtain the directional localization the DFT on the pseudo-polar grid is computed, and then one-dimensional band-pass filter is applied to the components of the signal with respect to this grid. More precisely, the definition of the pseudo-polar co ordinates $(u,v) \in$ R as follows:

$$(u,v) = (\xi_1,\frac{\xi_2}{\xi_1})\ f\ (\xi_1,\xi_2) \in D_0 \tag{6}$$

$$(u,v) = (\xi_1,\frac{\xi_1}{\xi_2})\ f\ (\xi_1,\xi_2) \in D_1 \tag{7}$$

$$g_j(u,v) = \hat{\mathrm{f}}_d^{\,j}(\xi_1,\xi_2)$$

After performing this change of co ordinates, is obtained and for $l = 1 - 2^j,...2^j - 1$:

$$\hat{f}(\xi_1,\xi_2) = \overline{V(2^{-2j}\xi_1,2^{-2j}\xi_2)}W_j^{(d)}(\xi_1,\xi_2) = g_j(u,v)\overline{W(2^j v - l)} \tag{8}$$

This expression shows that the different directional components are obtained by simply translating the window function W .The discrete samples $g_j[n_1,n_2] = g_j(n_1,n_2)$

are the values of the DFT of $f_d^j[n_1,n_2]$ on a pseudo-polar grid. That is, the samples in the frequency domain are taken not on a Cartesian grid, but along lines across the origin at various slopes. This has been recently referred to as the pseudo-polar grid. One may obtain the discrete Frequency values of f_d^j on the pseudo-polar grid by direct extraction using the Fast Fourier Trans-form (FFT) with complexity $O(N^2 \log N)$ or by using the Pseudo-polar DFT (PDFT).

4. Proposed Method

Texture features are very useful for classification usually be at various scales and directions. In many texture classification system including statistical and multi resolution based methods, the texture image cannot be efficiently analyzed at various scale and directions. Therefore, an efficient way to obtain a multi-resolution and multi-direction representation of texture images based on shearlet transform is proposed. The proposed method for texture classification system based on shearlet block based energy is shown in Figure 1. In general, a typical classification system mainly consists of two phases; feature extraction phase and classification phase.

4.1 Feature Extraction Stage

The most important part of any classification system is feature extraction. In this phase the texture properties that best distinguish the texture types are extracted. The extracted features contain sufficient information to allow distinctive and correct classification of texture types. To extract the features, the texture image is decomposed by NSST at various decomposition levels with multi-directions. The output of NSST based decomposition of a given texture image is a collection of sub-images called sub-bands. Each sub-band represents the components of the original image at specific directions and resolutions. From these sub-bands, the statistical information which characterizes the texture can be extracted to complete the feature extraction.

In the proposed system, energy is used to represent the textures. Energies can be measured by either magnitude or squaring the coefficients in the decomposed image. The energy of each directional sub-band is calculated by using the formula

$$\mathrm{ENERGY}_e = \frac{1}{RC}\sum_{i=1}^{R}\sum_{j=1}^{C}\left|I_e(i,j)\right|$$

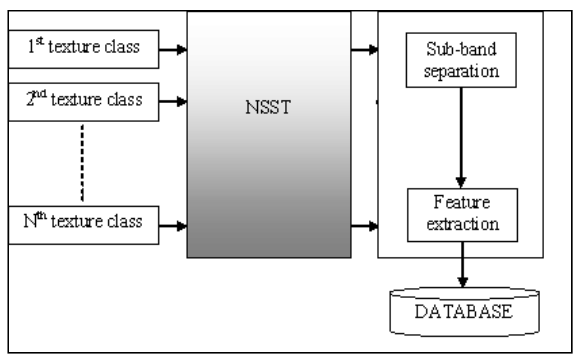

Figure 1: Feature Extraction stage of NSST

This process produces energy for sub-band B. The energies of all the sub-band are fused 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.

4.2 Classification Stage

In the classification stage, the same kind of features are extracted and compared with the database obtained in the feature extraction stage. Figure 2 shows the classification stage of the proposed system. The nearest neighbor classifier is designed to classify the unknown texture image into known texture class. The texture image to be classified is decomposed by using NSST and the feature vector is extracted as in the training phase. It should be noted that the number of decomposition level, number of directions and block size must be same in both the phases to avoid malfunction of classifier.

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The classification is done by using minimum distance measure. The Euclidean distance measure in (10) is used in the proposed method. 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

$$D(a,b)=\sqrt{(x_1-x_2)^2+(y_1-y_2)^2} \qquad (10)$$

The performance measure of the proposed texture classification system is the classification accuracy which is measured as the percentage of test set images classified into the correct texture class.

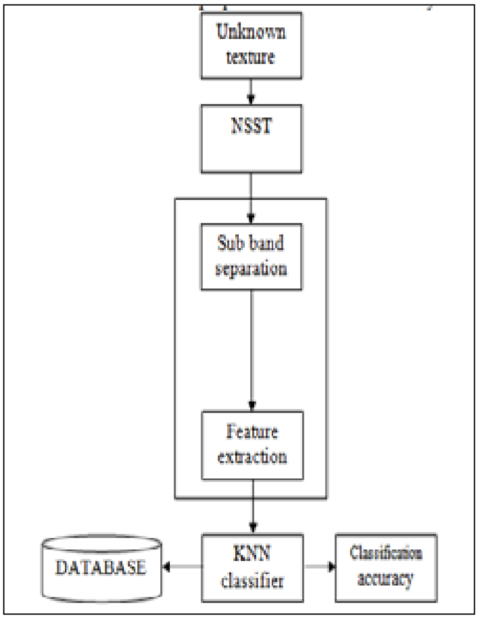

Figure 2: Classification stage of NSST

5. Experimental Results

In this section, the performance of the proposed texture classification algorithm based on NSST is described. The evaluation of the system is carried on Brodatz texture images [11]. The size of the Brodatz texture image is 640x 640 pixels and the images are gray scale images. The performance of the proposed system is compared with state art techniques in Linear Regression Modal (Zhi-Zhong Wang, Jun-Hai Yong, 2008), TSWT (T. Chang and C.C. J. Kuo, 1993), Gabor and GLCM (D. A. Clausi, H. Deng, 2005), Wavelet with GLCM (G. Van de Wouwer et al, 1999), Gabor transform (B. S. Manjunath, W. Y. Ma, 1996), F16b (R. Randen , J. H. Husøy,1999) and PSWT (S. Mallat,2003) To effectively compare the performance of the proposed system, the same 40 textures used by the above mentioned techniques is taken. Also the same number of training and testing images is used for each texture types.

Table 1: Classification accuracy of the proposed system using 2-level / 3-level NSST

Direction	Level 2	Level 3
D2	98.248	99.937
D4	99.312	99.937
D8	99.562	99.937
D16	99.749	99.937

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. Table 1 shows the overall classification accuracy obtained by the proposed system by 2 level and 3 level decomposition of NSST with multi-directions.

Table 2 shows the comparison between the proposed system based on NSST and wavelet transform. It is noted that the proposed system based on NSST provides higher classification accuracy of 99.937% than other state of art techniques. This is most probably due to the multi-directional selectivity of NSST over DWT. Because DWT has only some degree of directional selectivity in horizontal (High-Low), vertical (Low-High) and diagonal (High-High) sub-bands.

Table 2: Comparative analysis of the proposed system with other techniques in the literature

Methods	Classification Accuracy (%)
Gabor	43.43
Gabor and GLCM	48.99
PSWT	61.59
TSWT	79.17
F16b	90.06
Wavelet and GLCM	96.71
Linear Regression Model	97.15
Proposed method	99.937

6. Conclusion

In this paper, NSST based classification of Brodatz texture images is presented Experimental results show that the proposed system achieves 99.937%.The classification rate of the proposed system may be increased by varying the decomposition level and directions. Non subsampled shearlet transform based energy features provides better results than other methods.

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Classification accuracy