Asian Journal of Scientific Research

ISSN 1992-1454

Asian Journal of Scientific Research 7 (1): 94-101, 2014
ISSN 1992-1454 / DOI: 10.3923/ajsr.2014.94.101

Texture Classification by Shearlet Band Signatures

[1]C. Vivek and [2]S. Audithan
[1]PRIST University, Tanjore, Tamil Nadu, India
[2]Department of Computer Science, PRIST University, Tamil Nadu, India

Corresponding Author: C. Vivek, PRIST University, Tamil Nadu, India

ABSTRACT

Texture is a useful concept in both computer vision and image processing. Texture features that are useful for classification usually exist at various scales. In this study, an efficient approach to characterize textures based on Discrete Shearlet Transform (DST) is proposed. Texture classification is achieved by extracting entropy measure form the shearlet decomposed image. First, the texture image is decomposed by using DST and the proposed shearlet band signature, entropy is extracted from each sub-band of the decomposed image. These shearlet band signatures are used as features to classify the given texture image using K-Nearest Neighbor (KNN) classifier. The performance of the proposed system is analyzed by taking 40 Brodatz database texture images and compared with the methods based on statistical features, wavelet transform and Gabor transform. The results show that the classification accuracy of the proposed shearlet band signatures is 99.687% and the accuracy of this system very well compared to other state of art techniques.

Key words: Texture, image classification, discrete shearlet transform, entropy, nearest neighbor classifier

INTRODUCTION

Image texture is a key spatial attribute used in image processing and pattern recognition. It has received a considerable attention over the last few decades and the approaches to texture classification span a wide range of methods. Curvelet transform is applied by Arivazhagan *et al.* (2006) for classifying the texture images. From the sub-bands of curvelet transform, curvelet statistical features and curvelet co-occurrence features are extracted. The experimental result shows that the success rate is improved in comparison with traditional methods.

Classification of texture images based on Gaussian Markov Random Field model (GMRF) on linear wavelets is proposed by Reddy *et al.* (2010). Seven features are calculated from the wavelet transformed image by using least square error estimation method. For classifying texture, a novel scheme is introduced by Shen and Yin (2009) using curvelet transform. Mean and variance of the curvelet transform sub-bands are used as features. By the group features, discrimination can be found to classify texture images.

In order to improve the performance of texture classification system, three texture feature extraction method is described by Pharsook *et al.* (2011). Feature extraction method consists of gray level co-occurrence matrix and GMRF features. The classification is done by using Support Vector Machine (SVM). A detailed literature review is presented by Tou *et al.* (2009) for the classification of texture images based on various feature extraction techniques.

Three different methods, to classify texture images are presented by Arvis *et al*. (2004). The methods are multi spectral extension, joint colour texture features and grey scale texture features. Among the three methods multispectral gives the better results. An approach for colour texture classification by the use of Discrete Wavelet Transform (DWT), a multi-resolution analysis and neural network ensemble is investigated by Sengur (2009). The extracted features are Entropy and energy features.

DWT based texture classification is proposed by Hiremath and Shivashankar (2006). From, the sub band images the features are constructed. Euclidean distance and minimum distance classifier is used to classify an unknown texture image. This method gives the better classification rate at reduced computational cost. A wavelet based supervised classification model is proposed for classifying the texture by Aujol *et al*. (2003). In order to analyze the textures, energy distribution in each sub-band is used.

In this study, an efficient approach based on DST for gray texture classification is proposed. Texture information is captured by extracting entropy feature form the shearlet decomposed image. This study also gives a comparative analysis between the proposed systems with wavelet, Gabor and statistical based methods.

DISCRETE SHEARLET TRANSFORM

The most important step of any classification system is feature extraction. A new shearlet band signature, entropy is proposed based on discrete shearlet transform introduced by Easley *et al*. (2008). An N*N image consists of a finite sequence of values:

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

where, N∈ℕ. Identifying the domain with the finite group Z^2_N , the inner product of image x, y: $Z^2_N \to \mathbb{C}$ is defined as:

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

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

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

The brackets in the equations [·,·] denote arrays of indices, and parentheses (·,·) denote function evaluations. Then the interpretation of the numbers $f[k_1, k_2]$ as samples $f[k_1, k_2] = f(k_1, k_2)$ is given by the following equation from the trigonometric polynomial:

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

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 $f^j_a[n_1, n_2]$, 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 $f_a^0[n_1, n_2]$ is equal to $[n_1, n_2]$ has size N*N. In particular:

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

Thus, $f^j_d[n_1, n_2]$ are the discrete samples of a function $f^j_d[x_1, x_2]$ whose Fourier transform is $f^j_d(\xi_1, \xi_2)$. 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 $(u, v) \in R^2$ as follows:

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

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

After performing this change of co ordinates, $g_j\ (u,\ v) = f^j_d(\xi_1,\ \xi_2)$ is obtained and for $l = 1\text{-}2^j, \dots, 2^j\text{-}1$:

$$\begin{aligned}\hat{f}(\xi_1, \xi_2) &= \overline{V(2^{-2j}\xi_1, 2^{-2j}\xi_2)W_{jl}^{(d)}(\xi_1, \xi_2)} \\ &= g_j(u, v)\overline{W(2^j v - l)}\end{aligned} \tag{8}$$

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 $f^j_d[n_1, n_2]$ 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^j_d on the pseudo-polar grid by direct extraction using the Fast Fourier Trans-form (FFT) with complexity $ON^2\log N$ or by using the Pseudo-polar DFT (PDFT).

PROPOSED METHOD

The proposed method for texture classification based on shearlet band signature is shown in Fig. 1.

In general, a typical classification system mainly consists of two phases; feature extraction phase and classification phase. In the feature extraction phase, the features which characterize the given texture image is extracted. In the classification stage, the type of the unknown texture image

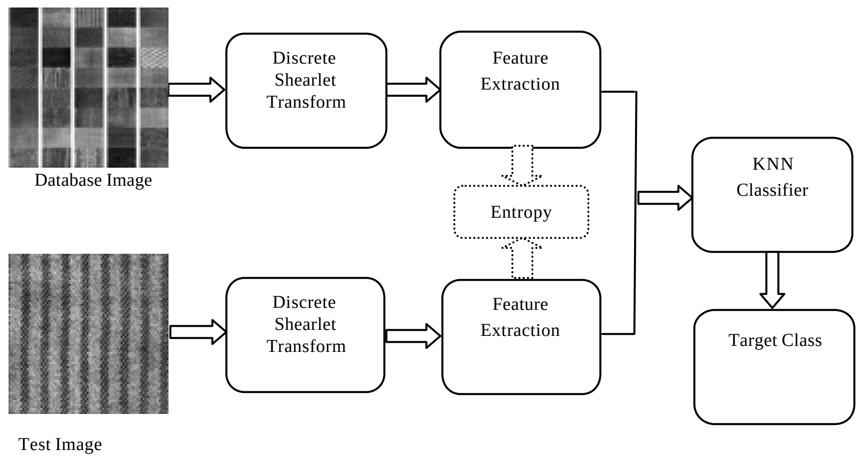

Fig. 1: Proposed texture classification system

is assigned to a known type by using the features extracted. The shearlet band signature, entropy is used to characterize the given texture image in the proposed system. To extract the signature, initially the decomposition of texture image is done by using DST. The decomposition produces a number of sub-bands which depends on the levels and directions used. From the sub-bands, the proposed shearlet entropy is extracted. Entropy is a geometric quantify of randomness of the texture of the input image. To calculate the entropy, the histogram of the sub-band image is generated. The zero entries in the histogram are removed and normalized. Then the entropy is calculated by the formula:

$$\text{Entropy} = -\sum_i p_i * \log(p_i) \tag{9}$$

where, p_i is the non zero histogram value. This process is carried out for all the sub-bands of the shearlet decomposed image. All the shearlet entropy signatures are combined together to make the feature set of the particular texture image. In the same way, feature set for all the texture images are extracted and stored for future reference.

The classifier used to assign a target class to an unknown texture image is KNN classifier. The proposed shearlet entropy features are extracted for the unknown texture image. Then the Euclidean distance metric is used to calculate the distance between the entropy features of the unknown texture image to the feature reference list. The reference texture image class which gives the minimum distance is assigned to the class of unknown texture image. The time consumption of the proposed classification is very low. The performance of the classification system is measured in terms of classification accuracy. This is measured as the percentage of test set images that are correctly classified into the same texture class.

EXPERIMENTAL RESULTS

The performance evaluation of the proposed texture classification system based on DST is carried on using Brodatz Album. The original size of the texture images in this album is 640x640 and all are 8 bit gray scale images. The proposed system is compared with other multi-resolution methods such as wavelet transform (Wang and Yong, 2008), Tree Structured Wavelet Transform

Table 1: Classification rate of the proposed texture classification system using 2-level DST

	No. of directions					
Texture ID	2	4	8	16	32	64
D6	95.122	100	100	100	100	100
D9	95.122	100	100	100	97.561	100
D11	92.6829	100	100	100	100	100
D16	100	100	100	100	100	100
D17	95.122	100	100	100	100	100
D20	100	100	100	100	100	100
D21	100	100	100	100	100	100
D22	75.6098	100	100	100	100	100
D24	92.6829	95.122	100	100	100	100
D26	100	100	100	100	100	100
D34	97.561	100	100	100	100	100
D36	85.3659	97.561	100	95.122	92.6829	85.3659
D41	95.122	90.2439	100	100	100	97.561
D46	92.6829	100	100	100	100	100
D47	92.6829	97.561	100	100	100	100
D51	90.2439	95.122	100	100	100	100
D53	100	100	100	100	100	100
D55	100	100	100	100	100	100
D56	100	100	100	100	100	100
D57	100	100	100	100	100	100
D64	100	100	100	100	100	100
D66	100	100	100	100	100	100
D68	100	100	100	100	100	100
D76	75.6098	92.6829	100	100	100	100
D77	100	100	100	100	100	100
D78	100	100	100	100	100	100
D79	90.2439	100	100	100	100	100
D80	82.9268	80.4878	100	100	100	100
D82	100	100	100	100	100	100
D83	80.4878	100	100	100	100	100
D85	48.7805	100	100	100	100	100
D101	43.9024	60.9756	82.9268	75.6098	100	53.6585
D102	78.0488	75.6098	87.8049	100	97.561	100
D103	100	100	100	100	100	100
D104	100	97.561	100	100	100	85.3659
D105	78.0488	85.3659	97.561	100	100	34.1463
D106	68.2927	85.3659	95.122	100	97.561	100
D109	97.561	100	100	100	100	100
D111	100	97.561	100	100	100	100
Average	90.8693	96.1851	99.0619	99.2495	99.6248	96.3102

(TSWT) (Chang and Kuo, 1993), Gabor transform (Manjunath and Ma, 1996), F16b (Randen and Husoy, 1999) and Pyramid Structured Wavelet Transform(PSWT) (Mallat, 2003). Also, the proposed method is compared with the combination of multi resolution methods with statistical based methods such as Gabor and GLCM (Clausi and Deng, 2005) and wavelet with GLCM (Van de Wouwer *et al.*,1999). The same technique in the aforesaid methods is used to extract the images and select the training and testing texture images.

Table 2: Classification rate of the proposed texture classification system using 3-level DST

	No. of directions					
Texture ID	2	4	8	16	32	64
D6	100	100	100	100	100	100
D9	100	100	100	100	100	100
D11	97.561	100	100	100	100	100
D16	100	100	100	100	100	100
D17	100	100	100	100	100	100
D20	100	100	100	100	100	100
D21	100	100	100	100	100	100
D22	100	100	100	100	100	100
D24	100	97.561	100	100	100	100
D26	100	100	100	100	100	100
D34	100	100	100	100	100	100
D36	97.561	100	100	100	100	100
D41	100	95.122	100	100	100	97.561
D46	100	100	100	100	100	100
D47	100	100	100	100	100	100
D51	97.561	100	100	100	100	100
D53	100	100	100	100	100	100
D55	100	100	100	100	100	100
D56	100	100	100	100	100	100
D57	100	100	100	100	100	100
D64	100	100	100	100	100	100
D66	100	100	100	100	100	100
D68	100	100	100	100	100	100
D76	100	100	100	100	100	100
D77	100	100	100	100	100	100
D78	100	100	100	100	100	100
D79	100	100	100	100	100	100
D80	100	100	100	100	100	100
D82	100	100	100	100	100	100
D83	100	100	100	100	100	100
D85	95.122	100	100	100	100	100
D101	100	100	97.561	100	100	100
D102	100	97.561	97.561	100	97.561	100
D103	70.737	68.2927	97.561	95.122	100	97.561
D104	78.0488	78.0488	95.122	100	100	97.561
D105	73.1707	95.122	82.9268	90.2439	90.2439	95.122
D106	75.6098	82.9268	97.561	97.561	100	100
D109	97.561	97.561	100	100	100	100
D111	100	100	100	100	100	100
Average	96.9981	97.7486	99.187	99.5622	99.6873	99.6873

From each original image, 128x128 pixel sized images are extracted with an overlap of 32 pixels between vertical and horizontal direction. From a single 640x640 texture image, 256 128x128 images are obtained. For the experiments, 81 images are randomly selected from the 256 images. Among the 81 images, 40 images are randomly chosen to train the classifier and the remaining images are used to test the classifier. In this experiment, 2 and 3-level shearlet transform with all possible direction is used to decompose the texture images. The performance of the proposed system

Table 3: Comparative analysis of the proposed system with other techniques in the literature

Methods	Classification accuracy (%)
Gabor and GLCM Clausi and Deng (2005)	48.995
Gabor Manjunath and Ma (1996)	43.429
PSWT Mallat (2003)	61.588
TSWT Chang and Kuo (1993)	79.166
Wavelet and GLCM Van de Wouwer *et al.* (1999)	96.707
F16b Randen and Husoy (1999)	90.061
Linear regression model Wang and Yong (2008)	97.151
Proposed method	99.687

is evaluated by varying the number of directions from 2 to 64. Table 1 and 2 shows the classification accuracy of the proposed texture classification system using shearlet entropy based on 2 and 3-level decomposition, respectively. As the number of levels and directions used in DST increases, the classification accuracy also increases. Since, DST is able to capture more information at higher directions. For 2-level decomposition, the classification accuracy increases from 90.87% (2 directions) to 99.62% (32 directions). The maximum classification accuracy achieved by 3-level decomposition with 32 directions is 99.68%. Table 3 shows the comparative analysis of the proposed system with other techniques in the literature in terms of classification accuracy. It is observed that the wavelet transform produces better performance than Gabor transform. Also the fusion of GLCM increases the classification accuracy. However, the proposed system based on DST outperforms all methods in terms of average classification accuracy.

CONCLUSION

In this study, shearlet band signatures based texture classification of 40 Brodatz texture images is presented. The decomposition of texture image is done by using 2 and 3-level DST with varying the direction from 2 to 64 at each level. Then the proposed shearlet band signatures, entropy of each sub-band are calculated. These shearlet based band signatures are used to characterize the training images and then used to classify the testing images. The proposed system consistently achieves over 99% classification accuracy for 2 and 3-level decomposition with 6 directions and above. Experimental results show that the proposed shearlet based texture classification system outperforms Wavelet and Gabor transform based classification systems.

REFERENCES

Arivazhagan, S., L. Ganesan and T.G.S. Kumar, 2006. Texture classification using curvelet statistical and co-occurrence features. Proceedings of the 8th International Conference on Pattern Recognition, August 20-24, 2006, Hong Kong, China, pp: 938-941.

Arvis, V., C. Debain, M. Berducat and A. Benassi, 2004. Generalization of the Co occurrence matrix for colour images: Application to colour texture classification. Image Anal. Stereol., 23: 63-72.

Aujol, J.F., G. Aubert and L. Blanc-Feraud, 2003. Wavelet-based level set evolution for classification of textured images. IEEE Trans. Image Process., 12: 1634-1641.

Chang, T. and C.C.J. Kuo, 1993. Texture analysis and classification with tree-structured wavelet transform. IEEE Trans. Image Process, 2: 429-441.

Clausi, D.A. and H. Deng, 2005. Design-based texture feature fusion using gabor filters and co-occurrence probabilities. IEEE Trans. Image Process., 14: 925-936.

Easley, G., D. Labate and W.Q. Lim, 2008. Sparse directional image representations using the discrete shearlet transform. Appl. Comp. Harm. Anal., 25: 25-46.

Hiremath, P.S. and S. Shivashankar, 2006. Wavelet based features for texture classification. J. Graphics Vision Image Process., 6: 55-58.

Mallat, S., 2003. A Wavelet Tour of Signal Processing. 2nd Edn., China Machine Press, Beijing, China, pp: 220?374.

Manjunath, B.S. and W.Y.Y. Ma, 1996. Texture feature for browsing and retrieval of image data. IEEE Trans. Pattern Anal. Machine Intell., 18: 837-842.

Pharsook, S., T. Kasetkasem, P. Larmsricha, S. Siddhichai, T. Chanwimaluang and T. Isshiki, 2011. The texture classification using the fusion of decisions from different texture classifiers. Proceedings of the 8th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, May 17-19, 2011, Khon Kaen, China, pp: 1003-1006.

Randen, T. and J.H. Husoy, 1999. Filtering for texture classification: A comparative study. IEEE Trans. Pattern Anal. Mach. Intell., 21: 291-310.

Reddy, B.V.R., M.R. Mani and K.V. Subbaiah, 2010. Texture classification method using wavelet transforms based on gaussian markov random field. Int. J. Signal Image Process., 1: 35-39.

Sengur, A., 2009. Color texture classification using wavelet transform and neural network ensembles. Arabian J. Sci. Eng., 34: 492-502.

Shen, L. and Q. Yin, 2009. Texture classification using curvelet transform. Proceedings of the International Symposium on Information Processing, August 21-23, 2009, Huangshan, China, pp: 319-324.

Tou, J.Y., Y.H. Tay and P.Y. Lau, 2009. Recent trends in texture classification: A review. Proceedings of the Symposium on Progress in Information and Communication Technology, December 7-8, 2009, Kuala Lumpur, Malaysia.

Van de Wouwer, G., P. Scheunders and D. Van Dyck, 1999.. Statistical texture characterization from discrete wavelet representations. IEEE Trans. Image Process., 8: 592-598.

Wang, Z.Z. and J.H. Yong, 2008. Texture analysis and classification with linear regression model based on wavelet transform. IEEE Trans. Image Process., 17: 1421-1430.