Journal of Applied Sciences

ISSN 1812-5654

science alert

ANSInet
an open access publisher
http://ansinet.com

Journal of Applied Sciences 14 (7): 697-702, 2014
ISSN 1812-5654 / DOI: 10.3923/jas.2014.697.702

Colour Texture Image Analysis by Shearlets

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

Abstract: In this study, a colour texture analysis approach using Discrete Shearlet Transform (DST) is proposed. The given colour texture image is effectively represented at various levels and directions by DST. From these representations, the shearlet band signatures energy and entropy are extracted and used as an input to K-Nearest Neighbor (KNN) classifier for classification. In order to analyze the proposed approach, 30 colour texture images obtained from VisTex is used. The classification accuracy obtained by the proposed shearlet band energy signature is 99.58% and the entropy signature is 100% which shows the texture discrimination power of DST. Also, the proposed approach is compared with state-of-art techniques based on statistical features, wavelet transform and contourlet transform.

Key words: Colour textures, discrete shearlet transform, entropy, energy, nearest neighbor classifier

INTRODUCTION

In computer vision and image processing, feature extraction is one of the important stages in gray and colour texture classification. Extensive researches have been proposed for the classification of texture images. A pair of quarter-size colour images directly from colour filter array images without any estimation is used to compute the Chromatic Co-occurrence Matrices (CCM) of these quarter-size images. This allows comparing textures by means of their CCM based similarity in texture classification or retrieval schemes, with the ability to use different colour spaces is presented in Losson and Macaire (2012). Chindaro *et al*. (2006) have explained a novel method that uses independent component analysis for systematically partitioning and combining textural features extracted from different colour spaces, in a multiple classifier based system, for colour texture classification.

Arivazhagan and Benitta (2013) have presented a new approach to extract the features of a color texture image for the purpose of texture classification. a four feature sets are involved to classify the texture features. Dominant neighbourhood structure is the new feature set that has been used for color texture image classification. Maia *et al*. (2010) have presented the contribution of the use of a texture-color combination in forest mapping. The spot image is transformed into different color spaces, then nine parameters using laws filter are extracted for color texture classification.

A new approach for color texture classification by use of Haralick features extracted from co-occurrence matrices computed from local binary pattern images is presented in Porebski *et al*. (2008). Features are extracted from color texture images which are coded in 28 different color spaces. The performances of two sequential feature selection schemes used for supervised color texture classification are compared in Porebski *et al*. (2010). They are sequential forward selection scheme and the more complex sequential forward floating selection scheme which avoids the “nesting effect”.

Akhloufi *et al*. (2007) gave an effective framework is proposed for color texture classification where statistical features are computed from a generalized isotropic co-occurrence matrix extracted from color bands and combined with image entropies. It is effectively tested in RGB, HSL and Lab color spaces. A new approach for color texture classification by use of Haralick features extracted from color co-occurrence matrices is explained by Porebski *et al*. (2007). This approach is to select the most discriminating color texture features in order to build a feature space with a low dimension.

An algorithm for classifying color textures using wavelet transform is described by Arivazhagan *et al*. (2005). Wavelet transform is useful for extracting texture features of images. A set of features are derived and color texture classification is done for different combination of the features and for different color models. The results obtained are found to be satisfactory. Sengur (2009) presented a composed of a wavelet domain feature

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

extractor and ensembles of neural networks classifier. Entropy and energy features are integrated to the wavelet domain feature extractor of the proposed color texture classification.

An integrative approach towards color texture classification and recognition using a supervised learning frame work is described in Giotis *et al*. (2012). This approach is based on generalized learning vector quantization extended by an adaptive distance measure. The proposed technique is evaluated by two sets of color texture images and compares results with those other methods achieved. A novel approach to colour texture classification based on combinations of the information included in different colour spaces is presented in Chindaro *et al*. (2003). It is an empirical study of decision combination approaches using classifiers obtained through training in various colour spaces and sub-spaces based on the features extracted using Gaussian Markov random fields.

A color texture retrieval system using a multi-resolution mosaic for flexible image classification is described in Guan and Wada (2002). Texture can be characterized by features such as shape, structure, color and randomness. A novel approach to color texture characterization and classification is proposed by Vertan *et al*. (2000). The reduced dimensionality color spaces are used for color texture characterization and classification. This color spaces allow a good classification performance by the use of classical energy-distribution features, defined in a scalar spectral domain. The proposed scheme composed of a wavelet domain feature extractor and an ANFIS classifier in Sengur (2008). Both entropy and energy features are used on wavelet domain.

DISCRETE SHEARLET TRANSFORM

The proposed texture classification approach is based on new multi-scale directional representations called the shearlet transform introduced by Glenn 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 $\mathbb{Z}_N^2$, the inner product of image $x, y: \mathbb{Z}_N^2 \to \mathbb{C}$ is defined as:

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

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

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

The brackets in the equations [·,·] denote arrays of indices and parentheses [·,·] denote function evaluations. Then, the interpretation of the numbers $\hat{f}[k_1, k_2]$ as samples $\hat{f}[k_1, k_2] = \hat{f}[k_1, k_a]$ is given by the following in Eq. 3 from the trigonometric polynomial:

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

First, to compute:

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

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 $f^{j-1}{}_a[n_1, n_2]$ and a high pass filtered image $f^j_d[n_1, n_2]$. Observe that the matrix $f^j{}_a[n_1, n_2]$ has size $N_j\times N_j$, where $N_j = 2^{-2j}$ and $f_a^0[n_1, n_2]$ has size N×N. In particular:

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

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 Discrete Fourier Transform (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 $(u, v)\in\mathbb{R}^2$ as follows:

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

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

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

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

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 with complexity $ON^2 \log N$ or by using the Pseudo-polar DFT.

PROPOSED METHOD

The proposed approach for colour texture classification based on shearlet transform is shown in Fig. 1.

Feature extraction is an important step for any classification system. In the proposed approach, the shearlet band signatures; energy and entropy are used as features for colour texture classification. The feature extraction process is as follows.

The input texture image is first decomposed by using the DST at different level of decomposition and directions. At first, the shearlet band signature, energy is computed for all sub-images by Eq. 9. The number of sub-images depends on the level and direction of DST:

$$E_k = \frac{1}{RC}\sum_{i=1}^{R}\sum_{j=1}^{C}|x_k(i,j)| \quad (9)$$

where, x_k (i, j) is the coefficient value of the kth sub-image and R, C is width and height of the sub-image, respectively. Then, the entropy signature is computed by Eq. 10:

$$\text{Entropy} = -\sum_i p_i * \log(p_i) \quad (10)$$

where, p_i is the non-zero histogram value. These features are used for the analysis separately. In order to train the classifier, predefined number of images per class is used. From the training images, the proposed features are extracted and they are used as an input to the classifier. The class of an unknown texture image is predicted by using nearest neighbour classifier. The distance parameters used in the classifier are Euclidean, city block, correlation and cosine matrices. Initially, the distance between the proposed features and features in the database are computed. Among the distances, the target class is assigned to the class of texture that has minimum distance. The parameter, classification accuracy is used to test the performance of the proposed approach.

EXPERIMENTAL RESULTS

The evaluation of the proposed approach is carried on the VisTex database (http://vismod.media.mit.edu/vismod/imagery/VisionTexture/vistex.html) texture images that consist of 30 colour textures of size 512×512. As the classifier needs training samples, each image in the database is subdivided into sub-images to create more samples of same texture image. The original image is divided into 128×128 non overlapping sub-images that produce 16 samples per class. Hence, there are 480 samples are available in total. Figure 2 shows the VisTex images used in this experiment.

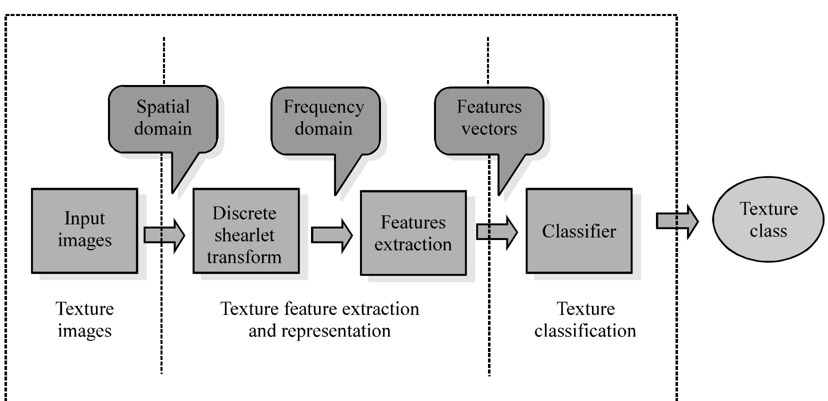

Fig. 1: Proposed texture classification system using discreat shearlet transform

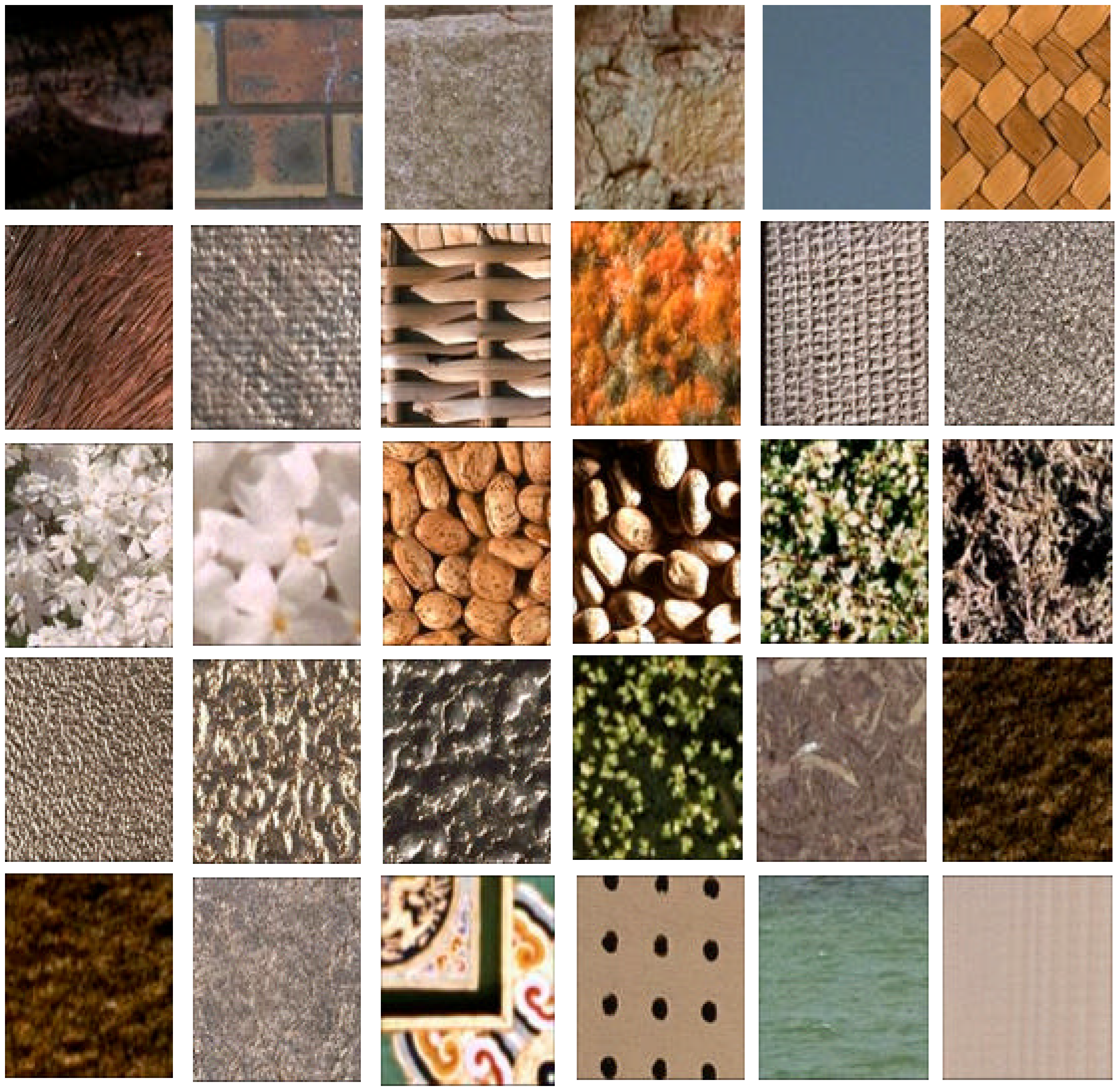

Fig. 2: VisTex colour texture image used in this experiment

In this experiment, KNN classifier is used to classify the unknown textures into known textures in the training database. The one nearest neighbor classifier is used i.e., k in the KNN classifier is set as 1. To train the classifier, 50% of images per class is used and the remaining 50% image per class is used for testing the classifier. To extract the features, 2 and 3-level shearlet transform with all possible direction is used. Table 1 and 2 shows the classification accuracy of the proposed approach using energy and entropy signatures based on 2 and 3-level decomposition, respectively. L represents the level of decomposition and D represents the number of directions used for the particular decomposition level.

The bold numerals in the tables show the maximum classification accuracy obtained by the proposed approach. Table 1 and 2 clearly show the dominance of entropy features over energy features as entropy signatures produces no misclassification irrespective of the levels and directions used. The number of features used in the classification task is chosen as one of the criteria as the speed of the classifier depends on this parameter. Table 3 shows the number of parameters in various combinations.

As the proposed approach achieves maximum classification accuracy at L2D2 which has the minimum number of features compared to other combinations. Hence, the proposed approach selects the L2D2 based shearlet entropy signatures and Euclidean distance/city block difference measure based KNN classifier for colour texture classification. To demonstrate the performance of

Table 1: Classification accuracy using 2-level discrete shearlet transform

Feature	KNN distance measure	L2D2	L2D4	L2D8	L2D16	L2D32	L2D64
Energy	Euclidean	92.50	92.08	92.08	92.08	91.67	91.66
	City block	95.83	97.08	97.50	97.91	97.91	98.75
	Correlation	90.00	92.91	94.16	93.75	94.16	94.16
	Cosine	97.50	97.50	97.50	97.50	97.50	97.50
Entropy	Euclidean	100.00	100.00	100.00	99.58	99.58	98.33
	City block	100.00	99.58	98.75	99.16	98.33	97.50
	Correlation	89.58	92.50	96.25	95.83	96.25	95.00
	Cosine	91.66	96.66	98.33	99.58	99.58	99.58

Table 2: Classification accuracy using 3-level discrete shearlet transform

Feature	KNN distance measure	L3D2	L3D4	L3D8	L3D16	L3D32	L3D64
Energy	Euclidean	93.33	93.75	94.16	94.16	94.16	93.75
	City block	97.08	98.75	99.16	99.16	99.58	99.58
	Correlation	95.83	95.83	96.66	97.50	97.08	97.50
	Cosine	99.16	99.16	99.16	99.16	99.16	99.16
Entropy	Euclidean	98.75	100.00	100.00	100.00	100.00	100.00
	City block	98.75	99.58	100.00	99.58	99.58	99.58
	Correlation	96.66	97.91	98.75	98.75	98.75	97.91
	Cosine	95.41	98.75	99.58	100.00	100.00	100.00

Table 3: No. of features extracted by various combinations of shearlet parameters

DST parameters	No. of features extracted	DST parameters	No. of features extracted
L2D2	5	L3D2	7
L2D4	9	L3D4	13
L2D8	17	L3D8	25
L2D16	33	L3D16	49
L2D32	65	L3D32	97
L2D64	129	L3D64	193

Table 4: Comparative analysis of the proposed system with state-of-art techniques

Method	Average classification rate (%)
Singular value decomposition (Selvan and Ramakrishnan, 2007)	41.17
Bit-plane probability (Choy and Tong, 2008)	96.79
Local binary pattern (Ojala *et al*., 2002)	97.13
Contourlet based (Dong and Ma, 2013)	99.25
Proposed method	100.00

the proposed system, the classification accuracy of the proposed approach is compared with four state-of-art techniques. They are based on different techniques such as contourlet transform (Dong and Ma, 2013), Local Binary Pattern (Ojala *et al*., 2002), bit-plane probability (Choy and Tong, 2008) and singular value decomposition (Selvan and Ramakrishnan, 2007). Table 4 shows the comparative analysis of the proposed system with the aforementioned techniques in terms of classification accuracy.

It is observed from the comparative analysis; the proposed shearlet based approach achieves 100% classification accuracy for 30 colour textures due to the texture representation capability of shearlet transform. Also, the above table shows the superiority of shearlet over contourlet (Dong and Ma, 2013) Local Binary Pattern (Ojala *et al*., 2002), bit-plane probability (Choy and Tong, 2008) and singular value decomposition (Selvan and Ramakrishnan, 2007). The proposed approach performs better than these methods by at least 0.75% on 30 VisTex colour images.

CONCLUSION

In this study, shearlet band signatures such as energy and entropy are analyzed for colour texture classification. These signatures are extracted from the colour texture images after decomposing it by using DST. The textural properties of images are taken at various decomposition level and directions. VisTex colour texture images are used for the analysis. Experimental results demonstrate the texture representation properties of DST which produces better accuracy for entropy features than the energy features. The maximum classification accuracy achieved by the energy is 99.58% where as the entropy features produce no misclassification. Also, the proposed approach is compared with other state-of-art techniques.

REFERENCES

Akhloufi, M.A., W.B. Larbi and X. Maldague, 2007. Framework for color-texture classification in machine vision inspection of industrial products. Proceedings of the International Conference on Systems, Man and Cybernetics, October, 7-10, 2007, Montreal, Canada, pp: 1067-1071.

Arivazhagan, S., L. Ganesan and V. Angayarkanni, 2005. Color texture classification using wavelet transform. Proceedings of the 6th International Conference on Computational Intelligence and Multimedia Applications, August 16-18, 2005, Las Vegas, Nevada, pp: 315-320.

Arivazhagan, S. and R. Benitta, 2013. Texture classification using color local texture features. Proceedings of the International Conference on Signal Processing Image Processing and Pattern Recognition, February 7-8, 2013, Coimbatore, pp: 220-223.

Chindaro, S., K. Sirlantzis and F. Deravi, 2003. Combining colour spaces: A multiple classifier approach to colour texture classification. Proceedings of the International Conference on Visual Information Engineering, July 7-9, 2003, Xi'an, China, pp: 109-112.

Chindaro, S., K. Sirlantzis and M.C. Fairhurst, 2006. ICA-based multi-colour space texture classification system. Elect. Lett., 42: 1208-1210.

Choy, S.K. and C.S. Tong, 2008. Statistical properties of bit-plane probability model and its application in supervised texture classification. IEEE Trans. Image Process., 17: 1399-1405.

Dong, Y. and J. Ma, 2013. Feature extraction through contourlet subband clustering for texture classification. Neurocomputing, 116: 157-164.

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

Giotis, I., K. Bunte, N. Petkov and M. Biehl, 2012. Adaptive matrices and filters for color texture classification. J. Math. Imaging Vision, 47: 79-92.

Guan, H. and S. Wada, 2002. Flexible color texture retrieval method using multi-resolution mosaic for image classification. Proceedings of the 6th International Conference on Signal Processing, Volume 1, August 26-30, 2002, Beijing, China, pp: 612-615.

Losson, O. and L. Macaire, 2012. Colour texture classification from colour filter array images using various colour spaces. Image Process., 6: 1192-1204.

Maia, H.E., A. Hammouch and M. Bakrim, 2010. Color texture feature selection by MIFS for image classification. Proceedings of the 5th International Symposium on I/V Communications and Mobile Network, September 30-October 2, 2010, Rabat, pp: 1-4.

Ojala, T., M. Pietikainen and T. Maenpaa, 2002. Multiresolution Gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans. Pattern Anal. Mach. Intell., 24: 971-987.

Porebski, A., N. Vandenbroucke and L. Macaire, 2007. Iterative feature selection for color texture classification. Proceedings of the International Conference on Image Processing, Volume 3, September 16 October 19, 2007, San Antonio, TX., pp: III-509-III512.

Porebski, A., N. Vandenbroucke and L. Macaire, 2008. Haralick feature extraction from LBP images for color texture classification. Proceedings of the 1st Workshops on Image Processing Theory, Tools and Applications, November 23-26, 2008, Sousse, pp: 1-8.

Porebski, A., N. Vandenbroucke and L. Macaire, 2010. Comparison of feature selection schemes for color texture classification. Proceedings of the International Conference on Image Processing Theory Tools and Applications, July 7-10, 2010, Paris, pp: 32-37.

Selvan, S. and S. Ramakrishnan, 2007. SVD-Based modeling for image texture classification using wavelet transformation. IEEE Trans. Image Process., 16: 2688-2696.

Sengur, A., 2008. Wavelet transform and adaptive neuro-fuzzy inference system for color texture classification. Expert Syst. Appl., 34: 2120-2128.

Sengur, A., 2009. Color texture classification using wavelet transform and neural network ensembles. Arabian J. Sci. Eng., 34: 491-502.

Vertan, C. and N. Boujemaa, 2000. Color texture classification by normalized color space representation. Proceedings of the 15th International Conference on Pattern Recognition, Volume 3. September 3-7, 2000, Barcelona, pp: 580-583.