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# Mosaic Texture Segmentation using Contourlet Transform

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**Abstract**

The main objective of this work is to segment a mosaic texture image using Contourlet Transform. The Contourlet Transform overcomes the drawback of minimum directionality of wavelet transform by providing multidirectionality with multiresolution. This paper utilizes numerous scales on sub-image by sub-image assessment of contourlet co-occurrence highlights for taking out the individuation and division of texture imags. In the proposed work, the image is subdivided into sub-images of size 32x32.The proposed system consists of i) preprocessing stage for denoising and sub-image separation, ii) CT based co-occurrence feature extraction and iii) fuzzy c means(FCM) clustering to provide the last segmented texture. The CT based segmentation provided good separation of mosaic texture regions. The segmentation results were compared with DWT based mosaic segmentation, the results shows that the ringing artifacts introduced in DWT based segmentation was reduced and also segmentation was accurate. The segmentation of mosaic texture can be employed in biomedical organ segmentation, satellite image segmentation etc.

***Keywords**: Contourlet Transform (CT), Contourlet co-occurrence features (CCF), Fuzzy C Means clustering (FCM).*

## 1. Introduction

Texture is a highlight that can assist in segmenting the images into subdivisions of segments, and to group those areas. In some imagery, it can be the negating representative of regions and perilous in attaining a particular investigation. Texture is routinely found in customary landscapes, for the most part in outdoors locates covering both typical and man-made things. Sand, stones, grass, leaves, squares, and various more examples show up in a texture. Textures are defined more than simply by their object classifications. Texture gives us confirmation about the spatial way of action of the shades or intensities in an image[1].

Through their texture, content texture analysis states the grouping of regions in an image. The in-built potentials are measured and defined by names as uneven, smooth, shiny, or bouncy as a motivation behind the spatial dissimilarity in pixel brightness. In such concern, the unevenness or bounciness means to dissimilarities in their intensity values, or gray levels. The texture analysis applications are applied to several areas, for example, geometrical recognizing, motorization, and handling medicinal images. Texture analysis is utilized to discover the texture borders, termed texture segmentation[2]. Texture analysis will be strong, while the objects in an image are classified further by its texture other than by intensity, so conventional thresholding techniques cannot be used viably.

The methods in texture analysis is separated into four groups[3] i) statistical methods[4] ,ii) geometrical methods[5,6], iii) Model base methods[7] and iv) signal processing methods[8].

A new texture segmentation method that uses contourlet cooccurrence feature is presented in this paper. Section II describes the proposed framework. In Section III the experimental results are discussed and in Section IV the proposed work is concluded.

# I. PROPOSED SYSTEM

The architecture of the proposed system is shown in Figure 1. Preprocessing, CT feature extraction and fuzzy clustering modules are included in the proposed framework.

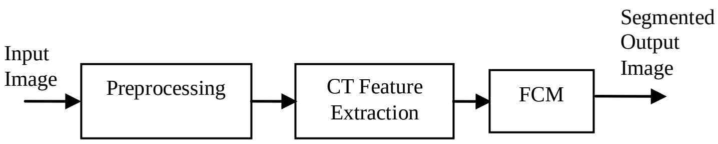


Figure 1. Proposed Block Diagram

## *A.* Preprocessing

The input image is preprocessed to enable fast processing and increase the segmentation accuracy. A median filter is used for filtering the input image to remove any noise present. The denoised image from the median filter is subdivided into blocks of size 32 x 32 from left to right.

## *B.* CT based feature extraction

A sparse expansion is obtained for natural images by initially applying a multiscale transform, next it is tailed by a local directional transform to gather the nearby basis functions at the similar scale into straight structures. Generally, we first utilize a wavelet-like transform for edge identification, and after that a nearby directional transform for contour segment recognition. Figure2 demonstrates a multiscale and directional disintegration utilizing a mix of a Laplacian pyramid (LP) and a directional filter bank (DFB).

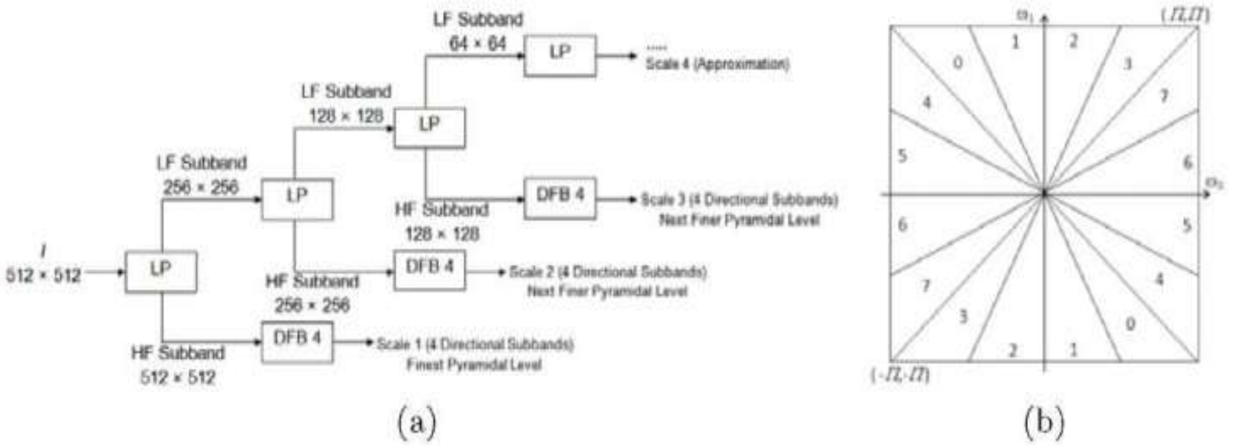


Figure 2. Decomposition of Image

The directional filter bank has an adaptable number of ways and it just captures the high frequency on the grounds, that the low frequencies of the input image are expelled before applying it. To compute a multiscale decomposition, we initially apply the Laplacian Pyramid. The down sampled lowpass image and the difference image of the next level can be computed in the same way. Then we can obtain a series of bandpass images. The Laplacian Pyramid decomposition can maintain a strategic distance from the frequency scrambling that occurs in the wavelet filter bank since it downsample the lowpass channel as it were. The directional filter bank is firstly decompose the directional image and have good performance in image reconstruction. While maintaining perfect reconstruction for expanding the decomposition tree, a simpler rule is used. One can decompose each scale into any arbitrary power of two's number of directions by applying the shearing operator combined with the two-channel quincunx filter bank at each node in a binary-structured bank.

It is true that the contourlet include all of the wavelet's advantages. The contourlet transform like wavelet transform is one of the pyramidal decomposition's methods. However, contourlet transform has other advantages compared to wavelet transform that can play the greater role for the applications of data hiding. Notwithstanding the wavelet transform which partitions the high recurrence just into three sub-groups at each level; it is conceivable to separate the high frequency into more sub-groups in the contourlet transform. This reality gives the assortment of sub-groups for embeding the secret data. Besides, regardless of the sub-groups in wavelet transform that are corresponded, the sub-groups in the contourlet transform are straightly free and subsequently uncorrelated. This could lead to more security in steganography. Because of the correlation between sub-bands in wavelet transform, each variation in a sub-band should cause changes in other sub-bands to be undetectable. Otherwise, there is the possibility of detecting by the steganalysis algorithms. Anyhow, as the sub-groups are straightly autonomous in contourlet, so there is lesser probability of identifying. In order to make optimal use of contourlet transform in image processing applications, we will have two important variables: The appropriate level of pyramid filters and the number of directional filters applied on the output. These two parameters are usually determined experimentally. In this work, the contourlet transform was carried out in level one, and as could be seen in Figure 2, the orthogonal directional filters are applied in four directions. Original image is decompose into 5 contourlet sub-bands, and each sub-band contains part of the original image frequency content. In fact, because of using orthogonal filters, these subbands will not overlap.

The mosaic textures of any size N x N can be taken as input. The examination can be done by taking sub band images of size n x n. In this work, the original input image considered is of 256 x 256 size. This original image is then divided into subimages of size 32 x 32, representing each submage using CT. Each n x n sub-image, taken from upper leftmost corner of the first image, is disintegrated utilizing single level CT and then the co-occurrence matrices are inferred from this for detail sub-bands. From the co- occurrence matrices obtained, the important CCFs, such as, contrast, correlation, energy and homogeneity, are calculated by using the relationships given in Eqs. (1)–(4), and are used as texture features[1,4].

$$\text{Contrast} = \sum_{i,j=0}^{N} (i-j)^2 C(i,j) \quad (1)$$

$$\text{Correlation} = \frac{1}{N-1}\sum\left(\frac{x-\bar{x}}{\sigma_x}\right)\left(\frac{y-\bar{y}}{\sigma_y}\right) \quad (2)$$

$$\text{Energy} = \sum_{i=1}^{N}\sum_{i=1}^{N} C(i,j)^2 \quad (3)$$

$$\text{Homogeneity} = \sum_{i,j=0}^{n} \frac{1}{\left(1+(i-j)^2\right)C(i,j)} \quad (4)$$

In equations (1) to (4), *i, j* are the horizontal and vertical cell coordinates of the coocurrence matrix C. Also $\bar{x}$, $\bar{y}$ , $\sigma_x$, and $\sigma_y$ respectively are the row wise and column wise mean and standard deviation of probability matrix along the row *x* and column *y*.

### *C.* Fuzzy C Means (FCM) Clustering

The input texture image is segmented based on the extracted features using, FCM clustering algorithm. The FCM technique minimizes a given objective function through an iterative improvement of the participation capacity based on the likeness between the successive information and the focal point of a cluster[11,12]. Also it changes the threshold between clusters through an iterative procedure. The objective function $J_m(U,v)$ and the membership function $u_{ik}$, used in FCM algorithm are characterized by the equations (5) and (6) given below.

$$J_m(U,v) = \sum_{k=1}^{n}\sum_{l=1}^{c} (u_{ik})^m (d_{ik})^2 \quad (5)$$

Where, $$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}}\right)^{2/(m-1)}} \quad (6)$$

In equations (5) and (6), $d^2_{ik}$ is the distance between the $k^{th}$ data and the centre of the $i^{th}$ cluster and $v_i$ denotes the centre value of the $i^{th}$ cluster, which are defined by equations (7) and (8) as follows:

$$d^2_{ik} = \|X_k - V_i\| \quad (7)$$

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$$v_i = \frac{\sum_{k=1}^{n} (u_{ik})^m x_k}{\sum_{k=1}^{n} (u_{ik})^m} \quad (8)$$

Where $x_k$ is the brightness value of the $k^{th}$ data, $n$ is the number of data, $c$ is the number of clusters, and $m$ is the exponent weight.

The proposed algorithm for segmentation of mosaic texture is outlined below:

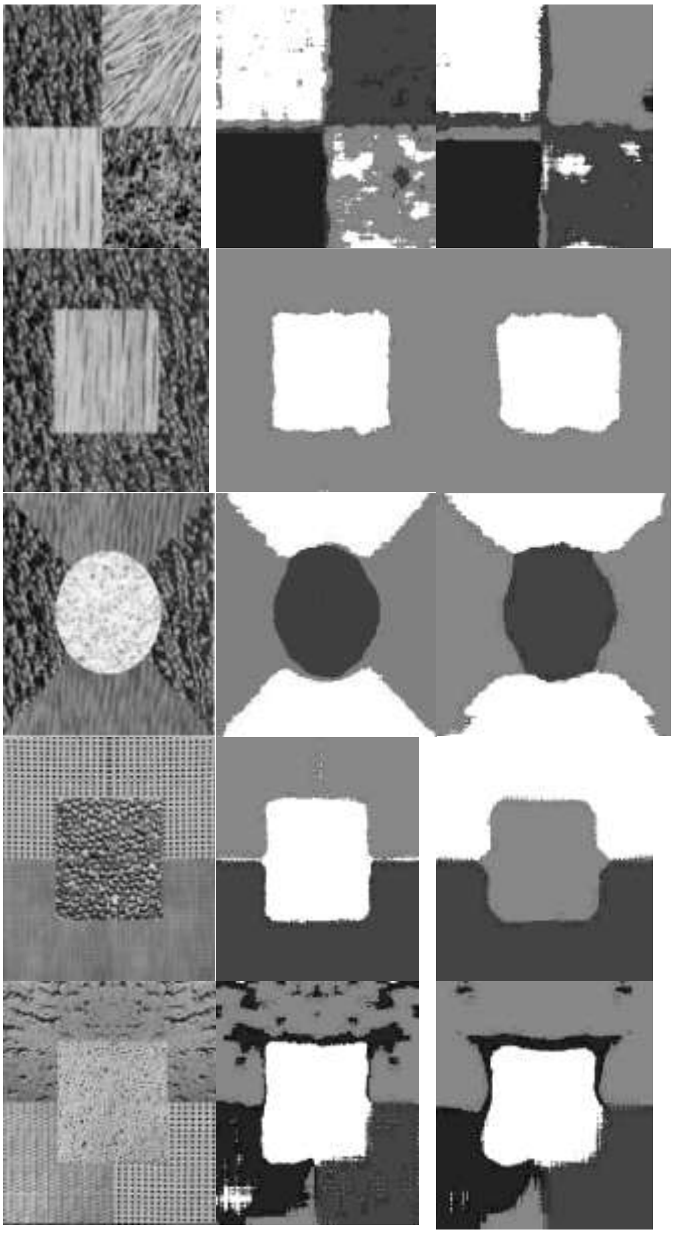
Step 1: Input the mosaic texture image of size N x N.
Step 2: Denoise the image by applying median filter.
Step 3: Obtain 32 x 32 sub-band images, beginning from the upper left end of the input image using CT.
Step 4: Generate co-occurrence matrices from the resulting detail sub-bands.
Step 5: Calculate the CCFs.
Step 6: Apply FCM clustering technique over the extracted features to generate the segmented mosaic texture

### *D.* Segmentation Evaluation

The segmented results are compared with ground truth using evaluation measures like Jaccard, Dice and Visual Overlap.

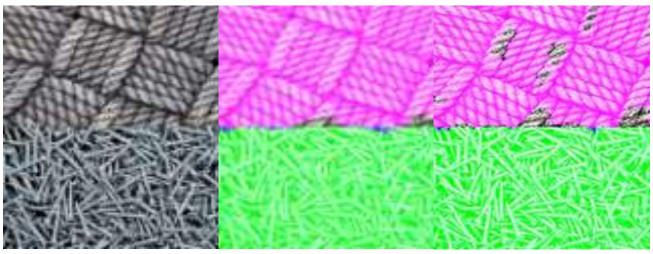
## III RESULTS AND DISCUSSION

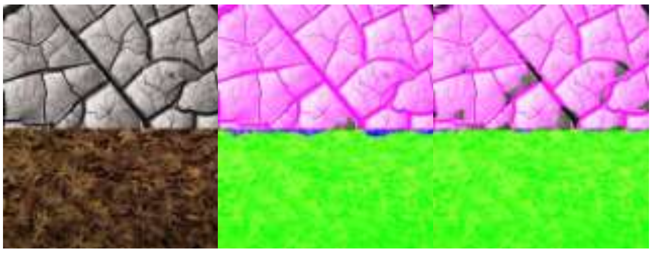
For experimentation, the segmentation method conversed in the previous subsection is used on five dissimilar mosaic texture images of size 256 x 256. The mosaic texture images taken for experimentation are shown in Figure 4(a), which comprise of five mosaic images. The test images consist of different kinds of textures. The segmented textures obtained using the proposed technique is also depicted in the Figure 4(b) and the results obtained by DWT based segmentation are shown in Figure 4(c). The texture segmentation by CT is more accurate than DWT based segmentation. This can be clearly seen from the Fig 4(b) and 4(c), black spots show the texture missed by the algorithm. The Visual Overlap of segmentation is shown in Figure 5, where the segmented results are superimposed over the original input images.



(a) (b) (c)

Figure. 4 Mosaic Segmentation for Two Images (a) Input Images, (b) Segmentation Using the Proposed Technique, (c) Segmentation using DWT





(a) (b) (c)

Figure. 5 Visual Overlap of Segmentation Results (a) Input Images, (b) Segmentation Results by Proposed Technique Superimposed on Inputs, (c) Segmentation Results by DWT Superimposed on Inputs

Table 1 shows the Jaccard coefficients obtained using DWT and CT based Segmentation.

| **Image** | **Contourlet Transform** | **Wavelet Transform** |
|---|---|---|
| Image 1 | 0.0018 | 0.0043 |
| Image 2 | 0.0025 | 0.0119 |
| Image 3 | 0.0021 | 0.0100 |
| Image 4 | 0.0011 | 0.0029 |
| Image 5 | 0.0010 | 0.0027 |

Table 2 shows the Dice coefficients obtained using DWT and CT based Segmentation.

| **Image** | **Contourlet Transform** | **Wavelet Transform** |
|---|---|---|
| Image 1 | 0.0037 | 0.0086 |
| Image 2 | 0.0050 | 0.0235 |
| Image 3 | 0.0041 | 0.0197 |
| Image 4 | 0.0025 | 0.0058 |
| Image 5 | 0.0023 | 0.0053 |

## REFERENCES

[1] Arivazhagan S, Ganesan L. Texture classification using wavelet transforms. Pattern Recognition Letters. 2003, 24 (9–10), pp. 1513– 1521.
[2] Guoliang Fan and Xiang-Gen Xia, Wavelet-Based Texture Analysis and Synthesis Using Hidden Markov Models. IEEE Trans. Circuits and Systems. 2003. Vol. 50, 106-120
[3] Katayoon Sarafrazi, Mehran Yazdi, Mohammad Javad Abedini. A New Image Texture Segmentation Based on Contourlet Fractal Features. Arab J Sci Eng. 2013. 38:3437–3449
[4] Tuceryan, M.; Jain, A.K.: Texture analysis. In: Chen, C.H.; Pau, L.F.; Wang, P.S.P. (eds.) The Handbook of Pattern Recognition and Computer Vision, 2nd edn, Chap. 2.1, pp. 207–248. World Scientific, Singapore (1998)
[5] Harpreet Singh, Shekhar Verma, Gaganpreet Kaur Marwah,“The New Approach for Medical Enhancement in Texture Classification and Feature Extraction of Lung MRI Images by using Gabor Filter with Wavelet Transform”,Indian Journal of Science and Technology,2015 Dec, 8(35), Doi no:10.17485/ijst/2015/v8i35/77238
[6] Haralick, R.M., Shanmugam, K.K., Dinstein, I., Texture features for image classification. IEEE Trans. Syst. Man Cyb. 8 (6), 1973. 610–621.
[7] Moran, P.A.P.: Notes on Continuous Stochastic Phenomena. Biometrika 37, 17–23 (1950)
[8] Geary, R.C.: The Contiguity Ratio and Statistical Mapping. Incorp. Statistician 3, 115–145 (1954)
[9] Swati Agarwal, A. K. Verma, Preetvanti Singh, Content Based Image Retrieval using Discrete Wavelet Transform and Edge Histogram Descriptor, IEEE Trans, Information Systems and Computer Networks, 2013. 19 - 23.
[10] F. Fanax Femy, S. P. Victor,“Comparative Evaluation of Contourlet and Wavelet Transform for Feature Extraction in Glaucoma Images”,Indian Journal of Science and Technology,2016 Mar, 9(13), Doi no:10.17485/ijst/2016/v9i13/90542
[11] N. Neelima, E. Sreenivasa Reddy, An improved image retrieval system using optimized FCM & multiple shape, texture features, IEEE Trans, Computational Intelligence and Computing Research , 2015. 1-7.
[12] Neeraja Menon ; Rohit Ramakrishnan, Brain Tumor Segmentation in MRI images using unsupervised Artificial Bee Colony algorithm and FCM clustering, IEEE Trans, Communications and Signal Processing, 2015,6-9.