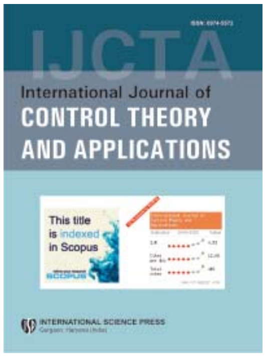

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Mosaic Texture Segmentation using Discrete Wavelet Transform

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Abstract: Texture segmentation and texture classification acts a key part in computer perception and framework identification; also it is broadly used to several regions such as mechanization, medical image handling and geometrical identifying. This paper uses many scales on subimage by subimage evaluation of wavelet co-occurrence features for taking out the individuation and separation of texture images. The input image is subdivided into subimages of size 32x32 in the proposed system. The proposed system consists of *i*) preprocessing stage for denoising and sub image division, *ii*) DWT based co-occurrence feature extraction and *iii*) fuzzy *c* means clustering to give the final segmented texture. The segmented results show good mosaic texture segmentation.

Keywords: *Discrete Wavelet Transform (DWT), Wavelet co- occurrence features (WCF), Fuzzy C Means clustering (FCM).*

1. INTRODUCTION

Texture is a highlight that can help to segment images into regions of interest and to categorize those regions. In some imagery, it can be the negating representative of regions and perilous in attaining a particular investigation. Texture is routinely seen in ordinary sceneries, mostly in open-air sights covering both normal and man-made items. Sand, stones, grass, leaves, blocks, and numerous more patterns make a textured appearance in images. Textures must be defined by more than simply their object classifications. Texture gives us evidence about the spatial course of action of the hues or intensities in an image[1].

Texture analysis states the grouping of regions in an image through their texture content. It tries to measure in-built potentials defined by names as uneven, smooth, satiny, or bouncy as a purpose of the spatial difference in pixel brightness. In such regard, the unevenness or bounciness denotes to dissimilarities in their intensity values, or gray levels. The application of texture analysis is applied to many areas such as geometrical identifying, mechanization, and medicinal image handling. Texture analysis is utilized to discover the texture borders, termed texture segmentation[2]. Texture analysis will be supportive while the objects in an image are further categorized by its texture than by intensity, and so conventional thresholding methods can't be utilized viably.

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

A texture segmentation method that use wavelet cooccurrence feature is proposed in this paper. Section II describes the proposed framework. Section III discusses the experimental results and Section IV gives the conclusion.

2. PROPOSED SYSTEM

The proposed system architecture is shown in Fig. 1. The proposed framework includes preprocessing, DWT feature extraction and fuzzy clustering modules.

Figure 1: Proposed Block Diagram

2.1. Preprocessing

Preprocessing enables fast and accurate processing of the input image. A median filter is used for filtering the input image to remove any noise present. The denoised image is divided into blocks of 32 x 32 sub images from left to right.

2.2. DWT based feature extraction

Wavelets Transforms are mathematical functions produced from one dimentional function Ψ by expansions and interpretations. The fundamental thought of wavelet based transform is to speak to any subjective function as a superposition of wavelets. Such superposition breaks down the specified function to various levels of different scales such that every level is again disintegrated with a determination adjusted to that particular level [1, 8].

To start with, the high-pass filter H and the low-pass filter L are used for every row data. The filtered data are then down-sampled by two to obtain high-and low- frequency coefficients of the row. Similarly, the high and the low-pass filters are applied again for every column data, and the results are down-sampled by two. The high frequency components are the detailed components and the low frequency components are the approximation components.

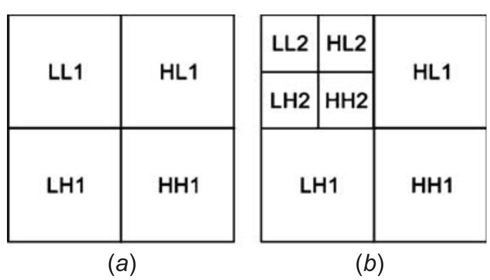

Figure 2: Decomposition of image: (*a*) first level, (*b*) second level

Thus by applying DWT over the input image, four sub-band images namely: HH, HL, LH, and LL are created. Every sub-band image will contain its own information level, for example, the low-frequency data or the approximation components are conserved in the LL-band, and the detailed component or high frequency data are practically conserved in the HH-, HL-, and LH-bands. The LL sub-band image can again be decomposed similarly to obtain the second level sub-band image. As shown in Fig.2, further decomposition of image into several level sub-bands is done by using 2-D DWT over the subsequent LL bands.

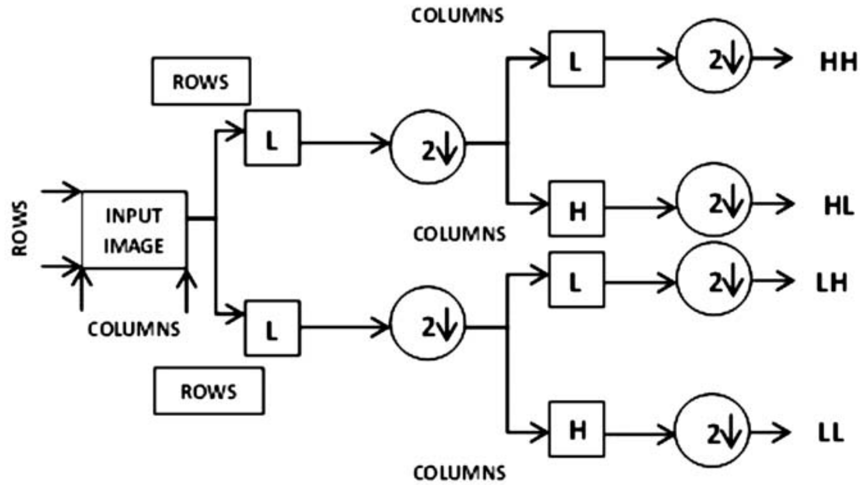

Figure 3: Single scale filter bank for first level decomposition

Initially the input image will be a single whole image. This image is properly divided into subimages by applying DWT. *i.e*., the image is decomposed into four sub-bands and at a very basic level as shown in Fig. 2(*a*). These four sub-band images are obtained by filtering and down sampling the image row-wise and then column-wise as shown in Fig. 3. The sub-bands marked LH1, HL1 and HH1 address the best detail components of the image while the sub-band marked LL1 relates to coarse level coefficients *i.e*., the estimated image. To attain the succeeding uneven level of wavelet coefficients, the sub-band LL1 only is again decomposed and essentially verified. This results in two level wavelet decomposition as depicted in Fig. 2(*b*). Likewise, to acquire extra decomposition, LL2 will be utilized. This procedure proceeds till the expected last scale is attained. The changed coefficients in estimated and sub-band images are the key elements, which are as significant for texture identification and segmentation. Generally the textures, either smaller scale or large scale, have non-uniform grey scale variations and they are quantifiably portrayed by the values of decomposed coefficients-changed sub band image or the components got from these sub-band images. Thus, the components got from these estimated and detail subimages strikingly portray a texture and these are valuable for texture analysis, namely segmentation.

The mosaic texture images of size N x N are taken as input. The examination is done through taking sub-images of size n x n. In this work, the original image is divided into subimages of size 32 x 32, representing each submage using DWT. Each *n* x *n* sub-image, taken from upper left corner of the first image, is disintegrated utilizing one level DWT and co-occurrence matrices are inferred for detail sub-bands, LH1, HL1 and HH1 of wavelet decomposed sub-image. From these co- occurrence matrices, important WCFs, such as, contrast, correlation, energy and homogeneity, are calculated by using the formulae given in Eqs. (1)–(4), as texture features[1,4].

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

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

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

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

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

2.3. Fuzzy C Means Clustering (FCM)

Texture is segmented from extracted features using, FCM clustering technique. FCM minimizes a given object function through the iterative improvement of the participation capacity in light of the likeness between the information and the focal point of a cluster [9, 10]. FCM changes the threshold between clusters through an iterative procedure the objective function $J_m(U, v)$ and the membership function u_{ik}, are characterized by the equations (5) and (6) given below.

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

Where

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

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:

$$d^2_{ik} = \| X_k - V_i \| \tag{7}$$

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

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 given 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 corner of the input image using DWT.

Step 4: Generate co-occurrence matrices from the resulting detail sub-bands.

Step 5: Calculate the WCFs.

Step 6: Apply FCM clustering technique over the extracted features to generate the segmented mosaic texture.

3. RESULTS AND DISCUSSION

For experimentation, the segmentation method conversed in the earlier section is used on five dissimilar mosaic texture images of size 256 x 256. The mosaic texture images taken for experimentation are shown in Fig. 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 Fig.4(b).

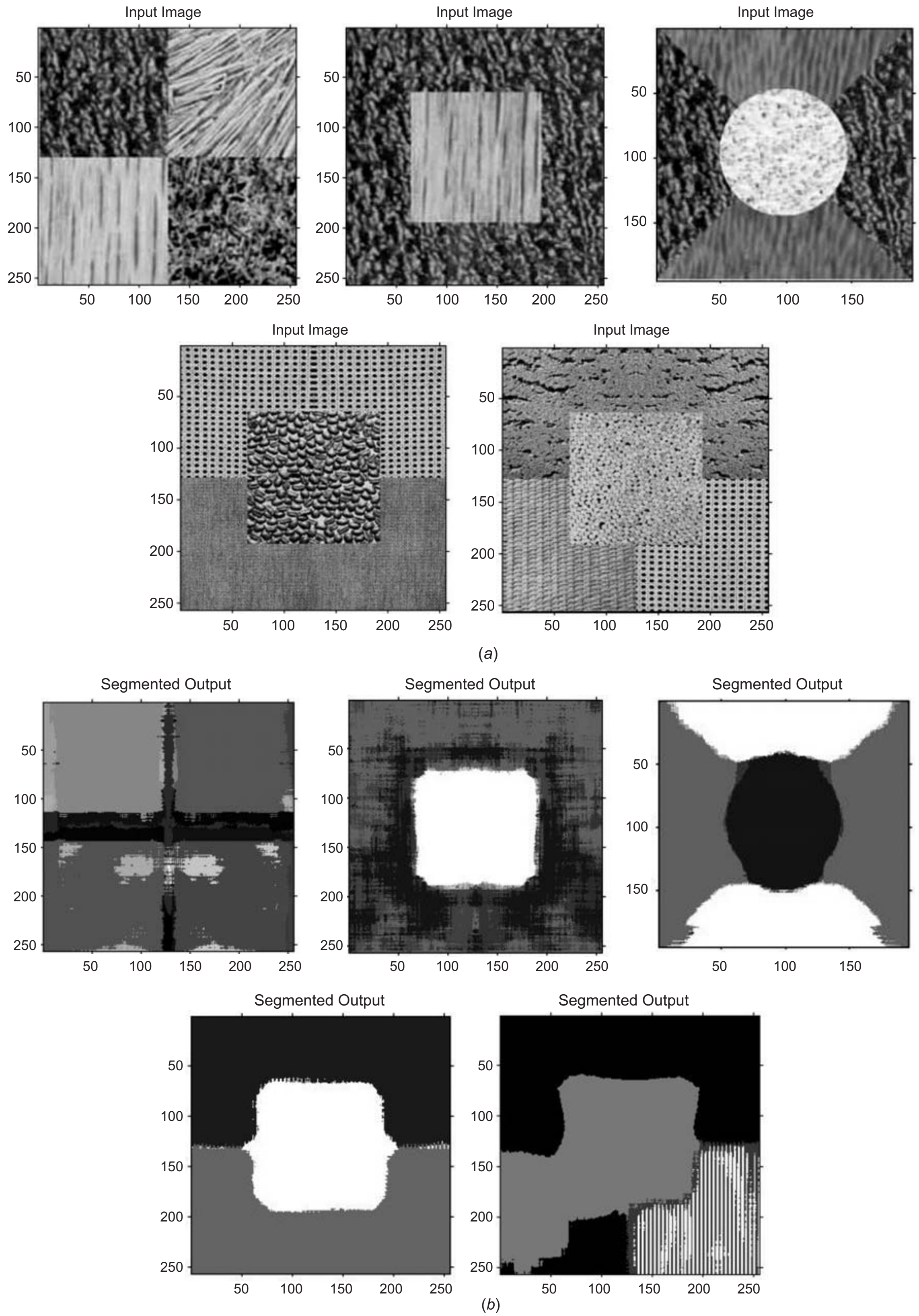

Figure 4: Results of Mosaic Texture Segmentation. (*a*) Input images. (*b*) Output Segmented Image

4. CONCLUSION

The idea of DWT applied over textured images for breaking them down into subtle element and estimate regions are discussed in this paper. In this work the denoised image is decomposed into subimages from which discrete wavelet transform based cooccurrence features are extracted. The extracted features are used by the clustering algorithm to perform the final segmentation, which produces the segmented image as output. The proposed algorithm segments the mosaic texture into separate regions which can be used in many applications.

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