Wavelet based Texture Segmentation methods based on Combinatorial of Morphological and Statistical Operations

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Summary
Texture analysis such as segmentation and classification plays a vital role in computer vision and pattern recognition and is widely applied to many areas such as industrial automation, bio-medical image processing and remote sensing. A segmentation scheme based on combinations of morphological and statistical operations is introduced in this paper on wavelet transformed images. Mathematical morphology is very attractive for this purpose because it efficiently deals with geometrical features like size, shape, contrast or connectivity that can be considered as segmentation oriented features. Derived equations on dilation, erosion and median or mean which finally results segmentation were applied on Harr, Db6, Cf6 and Sym8 wavelet transformed images. The present paper divides the wavelet combinatorial segmentation algorithm into three groups based on number of operations and type of operations, used. The present method using wavelet transforms is applied on Brodatz textures and a good segmentation is resulted.
Key words:
Geometrical features, Dilation, Erosion, Mean, Median, Dynamic, Number of operations and Type of operations.

1. Introduction

Analysis of texture requires the identification of proper attributes or features that differentiate the textures in the image for segmentation, classification and recognition. The features are assumed to be uniform within the regions containing the same textures. Initially, texture analysis was based on the first order or second order statistics of textures [15,29,11,13,7]. Then, Gaussian Markov random field (GMRF) and Gibbs random field models were proposed to characterize textures[9,6,18,22,8,20]. Later, local linear transformations are used to compute texture features [19, 24]. Then, texture spectrum technique was proposed for texture analysis [16]. The above traditional statistical approaches to texture analysis, such as co-occurrence matrices, second order statistics, GMRF, local linear transforms and texture spectrum, are restricted to the analysis of spatial interactions over relatively small neighborhoods on a single scale. As a consequence, their performance is best for the analysis of microtextures only [25].

More recently, methods based on multi-resolution or multi-channel analysis, such as Gabor filters and wavelet transform, have received a lot of attention [26,3,5,25,23,14,21,30,22,27]. But, the outputs of Gabor filter banks are not mutually orthogonal, which may result in a significant correlation between texture features. Finally, these transformations are usually not reversible, which limits their applicability for texture synthesis. Most of these problems can be avoided if one uses the wavelet transform, which provides a precise and unifying frame work for the analysis and characterization of a signal at different scales [25]. Another advantage of wavelet transform over Gabor filter is that the low pass and high pass filters used in the wavelet transform remain the same between two consecutive scales while the Gabor approach requires filters of different parameters [5]. In other words, Gabor filters require proper tuning of filter parameters at different scales. Later, Kaplan [17] proposed extended fractal analysis for texture classification and segmentation and Wang and Liu [28] proposed multi-resolution MRF (MRMRF) parameters for texture classification. Wavelet statistical features (WSF) and wavelet co-occurrence features (WCF) were proposed and effectively used for texture characterization and classification [2].

The wavelet transform is a multi-resolution technique, which can be implemented as a pyramid or tree structure and is similar to sub-band decomposition[1,10].There are various wavelet transforms like Haar, Daubechies, Coiflet, Symlet and etc. They differ with each other in the formation and reconstruction. The wavelet transform divides the original image into four subbands and they are denoted by LL(low-low), LH(low-high), HL(high-low) and HH(high-high) frequency subbands. The HH subimage represents diagonal details (high frequencies in both directions – the corners), HL gives horizontal high frequencies (vertical edges), LH gives vertical high frequencies (horizontal edges), and the image LL corresponds to the lowest frequencies. At the subsequent scale of analysis, the image LL undergoes the

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decomposition using the same filters, having always the lowest frequency component located in the upper left corner of the image. Each stage of the analysis produces next 4 subimages whose size is reduced twice when compared to the previous scale. i.e. for level '*n*' we get a total of '4+(n-1)*3' subbands. The size of the wavelet representation is the same as the size of the original.

The Haar wavelet is the first known wavelet and was proposed in 1909 by Alfred Haar. Haar used these functions to give an example of a countable orthonormal system for the space of square-integrable functions on the real line. The Haar wavelet's scaling function coefficients are *h{k}={0.5, 0.5}*and wavelet function coefficients are *g{k}={0.5, -0.5}*.

The Daubechies wavelets [10] are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function which generates an orthogonal multiresolution analysis.

The present paper initially decomposes the textures using the different wavelet transform for one level. Later the segmentation method has been applied on the decomposed images. For this the present paper is organized as follows. In the second section methodology is defined. In the third section results and discussions were given. The last section gives the conclusions.

2. Methodology

Many research scholars working in the area of morphology proposed many segmentation algorithms based on the orientation and type of Structuring Element (SE). But the present paper advocates a new method of segmentation of images, based on combinatorial approach of mathematical morphology and primitive statistical operations. A gray level image typically consists of both bright and dark object features with respect to size or scale. The basic objective of the present segmentation algorithm is to isolate or sketch out the most optimal contours of these bright and dark features. For this the present paper proposes three methods of segmentation based on number and type of operations. For this, the combinatorial segmentation schemes are divided into three groups. The segmentation of group one and group two consists of three coefficients purely based on morphological operation, and both morphological and statistical operations respectively. The segmentation scheme of group three consists of two coefficients based on both the types of operations. These segmentation approaches are derived in the form of equations. The Fig. 1 indicates a general model of texture segmentation using wavelets.

The mathematical representation for group one combinatorial segmentation is given in equations (1) and (2). The segmentation results depend upon the combinatorial coefficients of α, β and γ. This dependency is restricted to 95% by keeping the condition $\alpha > \beta$ and $\alpha > \gamma$.

$$S[i,j] = \alpha * D[i,j] - \beta * E[i,j] - \gamma * \frac{(D[i,j] - E[i,j])}{2} \ldots (1)$$

$$S[i,j] = \alpha * D[i,j] - \beta * E[i,j] - \gamma * \frac{(D[i,j] + E[i,j])}{2} \ldots (2)$$

D [i, j], E [i, j] represents Dilated and Eroded values of the 3×3 mask respectively, S [i, j] represents segmented grey level value of the mask.

The group two combinatorial segmentation is represented by equations (3) and (4).

$$S[i,j] = | \alpha * D[i,j] - \beta * E[i,j] - \gamma * Avg | \ldots.(3)$$

$$S[i,j] = | \alpha * D[i,j] - \beta * E[i,j] - \gamma * Med | \ldots.(4)$$

Where $\alpha > \beta$ and $\alpha > \gamma$, 'Avg' represents average value of the 3×3 mask and 'Med' represents median value of the 3×3 mask.

The segmentation of group three forms from the two operations of morphology and/or statistics. The mathematical representation for group three combinatorial segmentation is given in equations (5), (6), (7) and (8).

$$S[i,j] = [\alpha * D[i,j] - \beta * Avg] \ldots.(5)$$

$$S[i,j] = [\alpha * Avg - \beta * E[i,j]] \ldots.(6)$$

$$S[i,j] = [\alpha * D[i,j] - \beta * Med] \ldots.(7)$$

$$S[i,j] = [\alpha * Med - \beta * E[i,j]] \ldots.(8)$$

Where $\alpha \geq \beta$. This is needed to keep the resultant value of equations (5), (6), (7) and (8) as positive.

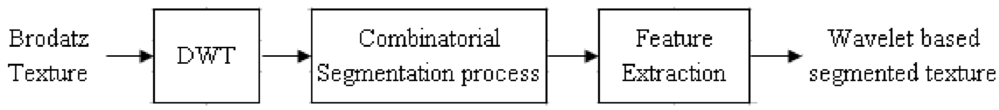


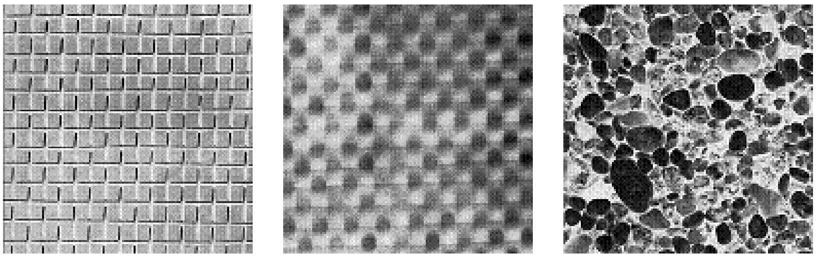
Fig. 1 Texture Segmentation system using wavelets.

3. Results and Discussions

The above group of morphological and statistical operations are applied using Haar, Db6, Cf6 and Sym8 wavelet transforms on 24 Brodatz textures[4]. However due to lack of space three Brodatz textures D_1, D_8 and D_{23} were chosen with dimensions of 256×256 and the original textures are displayed in Fig. 2.

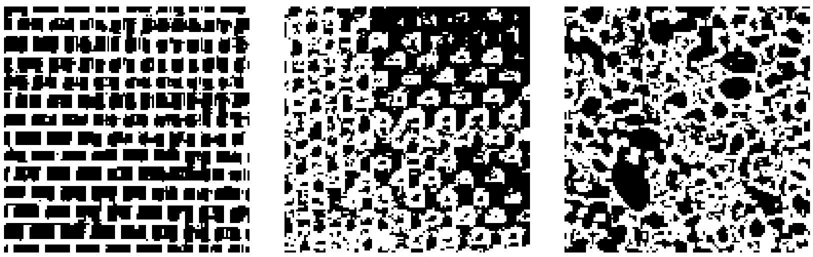
The validity of the proposed segmentation scheme is tested with different values of coefficients α, β and γ, on all four wavelet decomposed Textures D_1, D_8 and D_{23} using all the mathematical model equations from 1 to 8. Due to lack of space the segmentation scheme on few wavelets using Brodatz textures D_1, D_8 and D_{23} with different α, β and γ values are displayed from Figure 3 to Figure 10.

With equation1 and α, β and γ as 4, 3, 1 a good segmentation is resulted in all four wavelet transformed images. The equation 1 with α, β and γ as 4, 1, 3 has resulted into more number of white sparks with overlapped segmentation in all four wavelet transformed images. The equation 2 resulted a good segmentation than equation 1 for all the α, β and γ values for all four wavelet transformed images. In the same way, equation 3 and 4 resulted a good segmentation for all α, β and γ values on all wavelet transformed images. The equations 5, 6 and 7 resulted more and more overlapped regions with sparks.



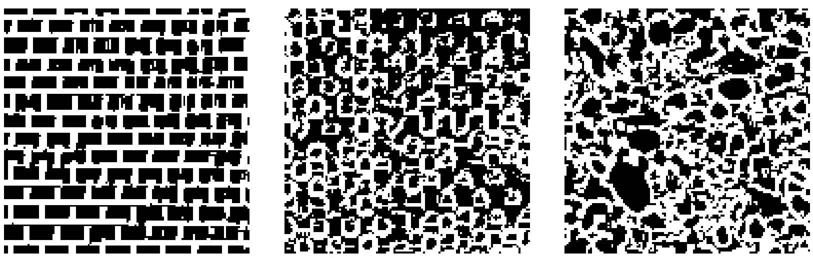
(a) (b) (c)

Fig. 2 Original Brodatz Textures (a)D_1 (b)D_8 (c)D_{23}.



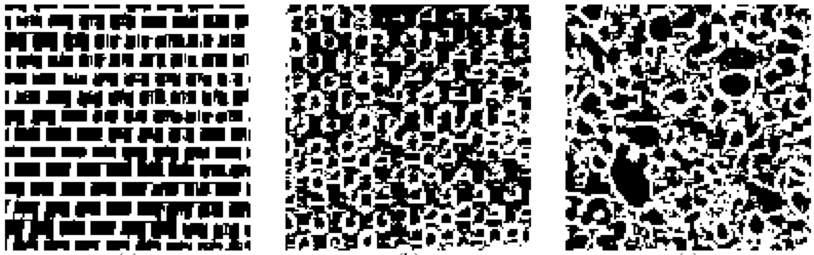
(a) (b) (c)

Fig. 3 Segmented textures resulted from group1 of equation1 using Haar wavelet transform. Where (a), (b) and (c) represents the segmented results of D_1, D_8 and D_{23} respectively when coefficients taken as (4,3,1).



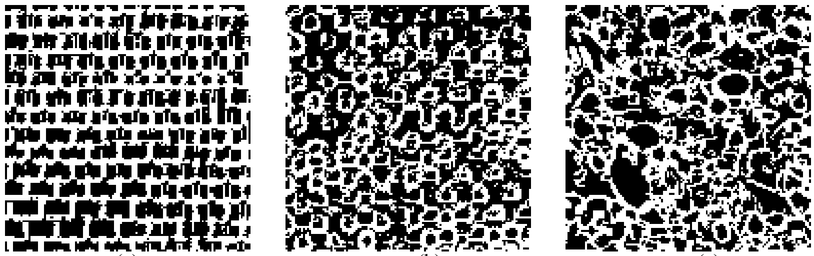
(a) (b) (c)

Fig. 4 Segmented textures resulted from group1 of equation2 using Db6 wavelet transform. Where (a), (b) and (c) represents the segmented results of D_1, D_8 and D_{23} respectively when coefficients taken as (4,1,3).



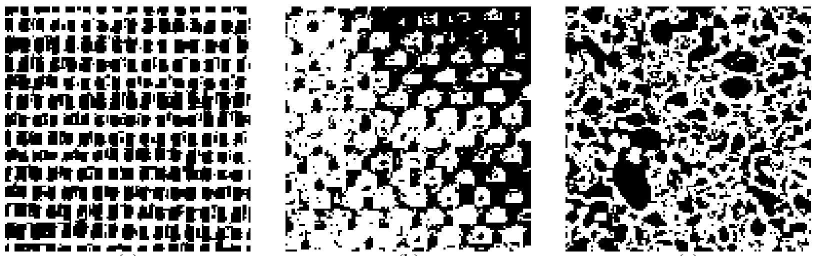
(a) (b) (c)

Fig. 5 Segmented textures resulted from group2 of equation3 using Cf6 wavelet transform. Where (a), (b) and (c) represents the segmented results of D_1, D_8 and D_{23} respectively when coefficients taken as (4,3,1).



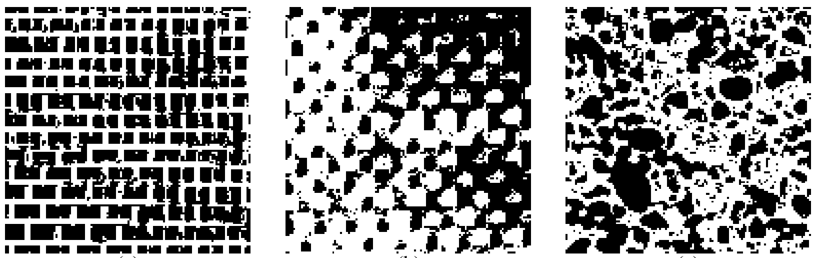
(a) (b) (c)

Fig. 6 Segmented textures resulted from group2 of equation4 using Sym8 wavelet transform. Where (a), (b) and (c) represents the segmented results of D_1, D_8 and D_{23} respectively when coefficients taken as (4,1,3).



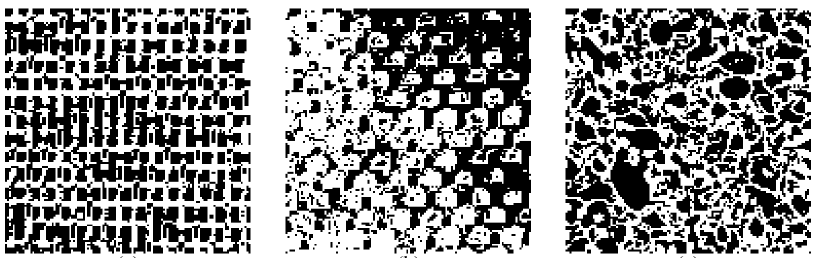
(a) (b) (c)

Fig. 7 Segmented textures resulted from group3 of equation5 using Haar wavelet transform. Where (a), (b) and (c) represents the segmented results of D_1, D_8 and D_{23} respectively when coefficients taken as (4,3).



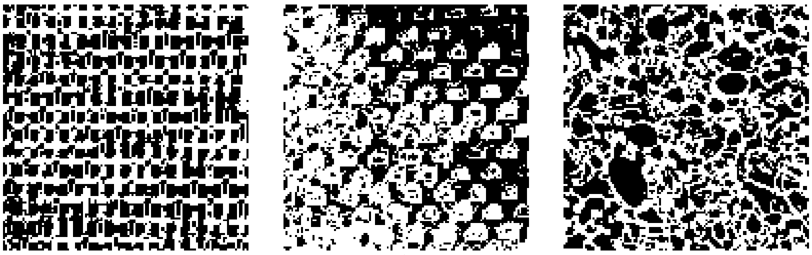
(a) (b) (c)

Fig. 8 Segmented textures resulted from group3 of equation6 using Db6 wavelet transform. Where (a), (b) and (c) represents the segmented results of D_1, D_8 and D_{23} respectively when coefficients taken as (4,3).



(a) (b) (c)

Fig. 9 Segmented textures resulted from group3 of equation7 using Cf6 wavelet transform. Where (a), (b) and (c) represents the segmented results of D_1, D_8 and D_{23} respectively when coefficients taken as (4,3).



(a) (b) (c)

Fig. 10 Segmented textures resulted from group3 of equation8 using Sym8 wavelet transform. Where (a), (b) and (c) represents the segmented results of D_1, D_8 and D_{23} respectively when coefficients taken as (4,3).

4. Conclusions

The present paper proposed eight different mathematical models for segmentation using simple morphological and statistical operations. These can be further extended. The segmentation scheme is dynamic because of α, β and γ parameters. The present segmentation methods after applying on 24 Brodatz textures on four wavelets concludes that the mathematical model with equations 2,3 and 4 have resulted into a good segmentation for all textures without any overlapping and noise.

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