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

V. Vijaya Kumar1†, U.S.N.Raju2††, M. Radhika Mani3†††, and A.L.Narasimha Rao 4††††

†Dean and Professor, Dept. of CSE and IT, Godavari Institute of Engg. and Technology, Rajahmundry, A.P., India
††Associate Professor in Computer Science and Engineering, GIET, Rajahmundry, A.P., India
†††Assistant Professor in Computer Science and Engineering, GIET, Rajahmundry, A.P., India
††††Associate Professor & Head, Dept. of CSE, Chaitanya Institute of Engg. and Tech., A.P., Rajahmundry, India

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, biomedical 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 framework 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 (vertical edges), and the image LL corresponds to the lowest frequencies. At the subsequent scale of analysis, the image LL undergoes the
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 multi-resolution 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 \( \alpha, \beta \) and \( \gamma \). This dependency is restricted to 95% by keeping the condition \( \alpha > \beta \) and \( \alpha > \gamma \).

\[
S[i, j] = \alpha \cdot D[i, j] - \beta \cdot E[i, j] - \gamma \cdot \frac{(|D[i, j] - E[i, j]|)}{2} \text{ \ ...(1)}
\]

\[
S[i, j] = \alpha \cdot D[i, j] - \beta \cdot E[i, j] - \gamma \cdot \frac{(|D[i, j] + E[i, j]|)}{2} \text{ \ ...(2)}
\]

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

\[
S[i, j] = |\alpha \cdot D[i, j] - \beta \cdot E[i, j] - \gamma \cdot \text{Avg}| \text{ \ ...(3)}
\]

\[
S[i, j] = |\alpha \cdot D[i, j] - \beta \cdot E[i, j] - \gamma \cdot \text{Med}| \text{ \ ...(4)}
\]

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 group three combinatorial segmentation 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).

\[
S[i, j] = |\alpha \cdot D[i, j] - \beta \cdot \text{Avg}| \text{ \ ...(5)}
\]

\[
S[i, j] = |\alpha \cdot \text{Avg} - \beta \cdot E[i, j]| \text{ \ ...(6)}
\]

\[
S[i, j] = |\alpha \cdot D[i, j] - \beta \cdot \text{Med}| \text{ \ ...(7)}
\]

\[
S[i, j] = |\alpha \cdot \text{Med} - \beta \cdot E[i, j]| \text{ \ ...(8)}
\]

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

The above group of morphological and statistical operations are applied using Haar, Db6, CIf6 and Sym8 wavelet transforms on 24 Brodatz textures[4]. However due to lack of space three Brodatz textures D1, D8 and D23 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 D1, D8 and D23, using all the mathematical model equations from 1 to 8. Due to lack of space the segmentation scheme on few wavelets using Brodatz textures D1, D8 and D23 with different α, β and γ values are displayed from Figure 3 to Figure 10.

With equation 1 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.

![Fig. 2 Original Brodatz Textures (a)D1 (b)D8 (c)D23.](image1)

![Fig. 3 Segmented textures resulted from group1 of equation1 using Haar wavelet transform. Where (a), (b) and (c) represents the segmented results of D1, D8 and D23 respectively when coefficients taken as (4,3,1).](image2)

![Fig. 4 Segmented textures resulted from group1 of equation2 using Db6 wavelet transform. Where (a), (b) and (c) represents the segmented results of D1, D8 and D23 respectively when coefficients taken as (4,1,3).](image3)
Fig. 5 Segmented textures resulted from group2 of equation3 using Cf6 wavelet transform. Where (a), (b) and (c) represents the segmented results of D1, D8 and D23 respectively when coefficients taken as (4,3,1).

Fig. 6 Segmented textures resulted from group2 of equation4 using Sym8 wavelet transform. Where (a), (b) and (c) represents the segmented results of D1, D8 and D23 respectively when coefficients taken as (4,1,3).

Fig. 7 Segmented textures resulted from group3 of equation5 using Haar wavelet transform. Where (a), (b) and (c) represents the segmented results of D1, D8 and D23 respectively when coefficients taken as (4,3).

Fig. 8 Segmented textures resulted from group3 of equation6 using Db6 wavelet transform. Where (a), (b) and (c) represents the segmented results of D1, D8 and D23 respectively when coefficients taken as (4,3).

Fig. 9 Segmented textures resulted from group3 of equation7 using Cf6 wavelet transform. Where (a), (b) and (c) represents the segmented results of D1, D8 and D23 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 $\alpha$, $\beta$ and $\gamma$ 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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References


Vakulabharanam Vijaya Kumar received integrated M.S Engg. degree from Tashkent Polytechnic Institute (USSR) in 1989. He received his Ph.D. degree in Computer Science from Jawaharlal Nehru Technological University (JNTU) in 1998. He has served the JNT University for 13 years as Assistant Professor and Associate Professor and taught courses for M.Tech students. He has been Dean for Dept of CSE and IT at Godavari Institute of Engineering and Technology since April, 2007. His research interests include Image Processing, Pattern Recognition, Network Security, Steganography, Digital Watermarking, and Image retrieval. He is a life member for CSI, ISTE, IE, IRS, ACS and CS. He has published more than 75 research publications in various National, Inter National conferences, proceedings and Journals.

U S N Raju received the B.E. (CSE) degree from Bangalore University in 1998. He worked as a Software Engineer in INDIGO RDBMS Research and Development for two years (1999-2000). After that he completed his M. Tech. (Software Engineering) from JNT University in 2002. He worked as an Academic Assistant in JNT University for six months and joined as an Assistant Professor in Mahatma Gandhi Institute of Technology, Hyderabad and worked there for five years (2002-2007). Presently he is working as an Associate Professor in Godavari Institute of Engineering and Technology, Rajahmundry. He is pursuing his Ph.D. from JNT University in Computer Science under the guidance of Dr V. Vijaya Kumar. He is a life member of ISTE and CSI.

M. Radhika Mani received the B.Tech (CSE) degree from Sir C.R. Reddy College of Engineering, Andhra University in 1998 and received her M. Tech. (Software Engineering) from Godavari Institute of Engineering and Technology (GIET), JNT University in 2008. Presently she is working as an Assistant Professor in GIET, Rajahmundry. Her areas of interest are Steganography, Watermarking and Image Processing. She has published 1 research publications in Inter National Journal, 1 in International Conference and 2 in National conferences.

A.L.Narasimha Rao received the B-Tech. (CSE) degree from Nagpur University in 1997. He worked as an Assistant Professor in AVANTHI PG college for one year (1998-1999). After that he completed his M. Tech. (CSE) from Osmania University in 1999. He worked as an assistant professor in MOTHER TERESSA Engineering college for 3 years, joined as an Assistant Professor in Pretorea university South Africa and worked there for two years (2002-2004) and worked as an Associate professor in Holy Mary Institute of Science & Technology 3 years (2004-2007). Presently he is working as an Associate Professor in Chaitanya Institute of Engineering and Technology, Rajahmundry. He has published research papers in various National, Inter National conferences, proceedings and Journals.