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# Adaptive Texture Segmentation using M Band Wavelet Transform and Wavelet Packet

Taramati Taji, Deipali Gore

*Computer Engineering Department, Savitribai Phule Pune University*
*PES Modern College of Engineering, ,Shivajinagar,Pune-411005.*

*Abstract*— **The *M*-band wavelet decomposition, which is a direct generalization of the standard 2-band wavelet decomposition is applied to the problem of an unsupervised segmentation of different texture images. Orthogonal and linear phase *M*-band wavelet transform is used to decompose the image into *M*X*M* channels. Various sections of these bandpass sections are combined to obtain different scales and orientations in the frequency plane. Texture features are extracted by applying each bandpass section to a nonlinear transformation and computing the measure of energy in a window around each pixel of the filtered texture images. Then the window size is adaptively selected depending on the frequency content of the images. Unsupervised texture segmentation derived by combination of different clustering and feature extraction techniques is compared.**

*Keywords*— **Discrete Wavelet Transform, M-band WT, Discrete Wavelet Packet, K Means, FarthestFirst.**

## I. Introduction

Computer Vision encompasses an important task of texture analysis. Various applications like image retrieval based on content, medical diagnosis, satellite imaging make use of texture analysis. The idea of segmenting a given image into meaningful segments based on the criterion of textural cue is referred to as "*Texture Segmentation*". In this paper we investigate the segmentation accuracy obtained by M-Band wavelet transform and Wavelet packet approaches and compare the obtained results with traditional Discrete Wavelet Transform. Mausumi Acharyya and Malay Kundu [1] have analyzed texture segmentation technique using M band which is a generalization of standard 2 band wavelet decomposition. They used multichannel filtering approach which seems attractive as it exploits variations in dominant sizes and orientations of various textures. Different filtering techniques like isotropic filters [2] discrete cosine transform (DCT) [3] Gabor filters [4] for successful application of multichannel filtering are studied. Use of Multi Resolution Analysis (MRA) technique for multiresolution signal decomposition by Mallat [5] was done successfully. He used Quadrature Mirror Filters (QMF) to relate description at various scales of decomposition of the embedded subspace representation. Standard wavelets suffer from a serious drawback that they are not suitable for the analysis of high frequency signals with relatively narrow bandwidth. So the main theme of this paper is to use the M-Band decomposition scheme which yields better segmentation accuracies. The octave band wavelet decomposition indicate finer frequency resolution in the low-frequency region than in the high-frequency region. Studies indicate that the texture features are more dominant in the intermediate frequency band.

The system set-up for the texture segmentation algorithm is demonstrated in Fig. 1. The image is first wavelet transformed into *M*X*M* channels by applying the *M*-band transform, without downsampling which gives an overcomplete representation of the image. Then different combinations of these bandpass sections are taken to obtain different scales and orientations in the frequency plane. In the second step, a local energy estimator consisting of a nonlinear operation and a smoothing filter, is applied to the various combinations of these bandpass areas. The area of the smoothing window is determined dynamically based on the spectral frequency content of the images. These steps give the texture features that can be classified successfully. The use of overcomplete wavelet representation removes the problem of inaccurate edge localization of the texture elements and discrepancies in detection of boundaries of different texture classes.

The organization of the paper is as follows. Section 2 briefly explains the wavelet transform and *M*-band wavelet transform. Section 3 presents the analysis of the multichannel filtering technique used in the proposed texture segmentation scheme, extraction of features and further discusses the merging of these extracted features. In section 4 we give experimental results and in section 5 we give conclusion of the present work.

## II. Wavelet Transform And M-Band WT

### A. Discrete Wavelet Transform

The *wavelet transform* is a signal decomposition onto a set of basis functions called wavelets. The wavelets are obtained from a single-prototype function by scalings and shifts [5,6]. This is the standard 2-band wavelet transform. Wavelet transform of a 1-D signal $f(x)$ is defined as,

$$Wf_a(b) = \int f(x)\, \psi^*_{a,b}(x)\, dx \qquad (1)$$

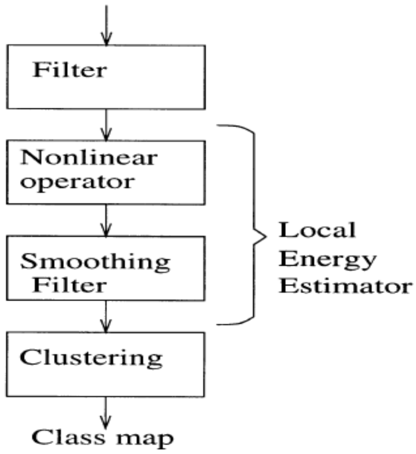



Fig. 1. Proposed System for Texture Segmentation

where $\psi$ is the mother wavelet and $a$ and $b$ are dilation and translation parameters respectively. The discrete wavelet expansion of a signal $f(x) \in l_2$ ($l_2$ is the space of square summable functions) is given as,

$$f(x) = \sum_{k\epsilon z} S_{J,k}\, \phi_{J,k}(x) + \sum_{j=1}^{J} \sum_{k \in Z} d_{j,k}\, \psi_{j,k}(x) \qquad (2)$$

where $\phi$ and $\psi$ are the scaling and wavelet functions, respectively and are associated with the analyzing (or synthesizing) filters $h$ and $g$. $d_{j,k}$'s are the wavelet coefficients and $S_{J,k}$'s are the expansion coefficients of the coarser signal approximation of $f(x)$.

*B. M-Band Wavelets*

The *M*-band wavelets zoom in onto narrowband high-frequency components of a signal and give better energy compaction than 2-band wavelets [7]. There are $M$-1 wavelets, $\psi_i(x)$, $i$=1,2,...,$M$-1 associated with the scaling function. For any function $f(x) \in L^2(R)$, it can be shown that,

$$f(x) = \sum_{i=1}^{i=M-1} \sum_{j\epsilon z} \sum_{k\epsilon z} < f(x)\psi_{i,j,k}(x) > \psi_{i,j,k}(x) \quad (3)$$

The $\psi_{i,j,k}(x)$ functions are obtained by scaling and shifting the corresponding wavelet $\psi_i(x)$:

$$\psi_{i,j,k}(x) = M^{j/2}\ \psi_i(M^j x - k) \qquad (4)$$

where i = 1,2,……M-1, k ∊ Z, j ∊ Z

Given a scaling function $\psi_0(x)$ in $L^2(R)$, the wavelet functions are defined as,

$$\psi_i(x) = \sqrt{M} \sum_{k=0}^{k=N-1} h_i(k)\psi_o(Mx - k) \qquad (5)$$

*C. Multiresolution Analysis*

The scaling function and the *M*-1 wavelet functions also define a multiresolution analysis [8]. A multiresolution analysis is a sequence of approximation spaces for $L^2(R)$. If the space spanned by the translates of $\psi_i(x)$ for fixed $j$ and $k \in Z$ is defined by $W_{i,j}$ = Span { $\psi_{i,j,k}$ }, then it can be shown that,

$$Wo_{,j} = \oplus_{i=0}^{M-1}\ W_{i,j-1} \qquad (6)$$

$$\lim_{j\to\infty} Wo_{,j} = L^2(R) \qquad (7)$$

Thus the $W_{0,j}$ spaces form a multiresolution space for $L^2(R)$. An important aspect of *M*-band wavelets is that a given scaling filter $h_0$ specifies a unique $\psi_0(x)$ and consequently a unique multiresolution analysis.

## III. Texture Feature Extraction

The feature extraction method involves multichannel filtering, followed by a nonlinear stage and then by a smoothing filter which constitute the local energy estimator as shown in Fig. 1. The objectives of filtering and that of the local energy estimator are to transform the edges between textures into detectable discontinuities.

*A. M-Band Wavelet Filters*

The filter bank in essence is a set of bandpass filters with frequency and orientation specific properties. In the filtering stage we make use of orthogonal and linear phase *M*-band wavelet transform [1] to decompose the texture images into *MXM* channels, corresponding to different direction and resolutions. In this work we have obtained the $M^2$-channel 2-D separable transform by the tensor product of *M*-band 1-D wavelet filters but without downsampling, which are denoted by $\psi_{i,j}$ for $i, j$=1,2,3,4 with $M$=4. The $i,j^{th}$ resolution cell is obtained via the filtering step $H_{i,j} = \psi_{i,j}\, \psi^*_{i,j}$ for $i, j$=1,2,3,4 with $M$=4. The decomposition of the image into *MXM* (=16) channels is illustrated in Fig. 2.

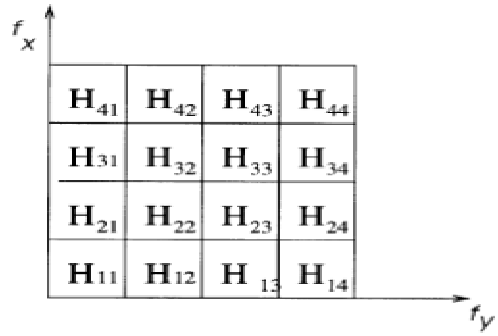



Fig. 2. Frequency bands corresponding to decomposition filters

We can perform edge detection by using 2-D filtering as follows:

- *Horizontal edges*: are detected by highpass filtering on columns and lowpass filtering on rows.
- *Vertical edges*: are detected by lowpass filtering on columns and highpass filtering on rows.
- *Diagonal edges*: are detected by highpass filtering on columns and highpass filtering on rows.
- *Horizontal-diagonal edges*: are detected by highpass filtering on columns and lowpass filtering on rows.
- *Vertical-diagonal edges*: are detected by lowpass filtering on columns and highpass filtering on rows.

The decomposition filters are formed as follows for different directions in increasing level of resolutions.

*Horizontal direction*:

$\mathbf{Filt_{hor1} = H_{12}}$,
$\mathbf{Filt_{hor2} = H_{12} + H_{13}}$,
$\mathbf{Filt_{hor3} = H_{12} + H_{13} + H_{14} + H_{24}}$.

*Vertical direction*:

$\mathbf{Filt_{ver1}} = \boldsymbol{H_{21}}$,
$\mathbf{Filt_{ver2}} = \boldsymbol{H_{21} + H_{31}}$,
$\mathbf{Filt_{ver3}} = \boldsymbol{H_{21} + H_{31} + H_{41} + H_{42}}$.

*Diagonal direction*:

$\mathbf{Filt_{diag1}} = \boldsymbol{H_{22}}$,
$\mathbf{Filt_{diag2}} = \boldsymbol{H_{22} + H_{33}}$,
$\mathbf{Filt_{diag3}} = \boldsymbol{H_{22} + H_{33} + H_{44}}$.

*Horizontal-diagonal direction*:
$\mathbf{Filt_{hdiag1}} = \boldsymbol{H_{12}}$,
$\mathbf{Filt_{hdiag2}} = \boldsymbol{H_{12}} + \boldsymbol{H_{23}}$,
$\mathbf{Filt_{hdiag3}} = \boldsymbol{H_{12}} + \boldsymbol{H_{23}} + \boldsymbol{H_{34}}$.

*Vertical-diagonal direction*:
$\mathbf{Filt_{vdiag1}} = \boldsymbol{H_{21}}$,
$\mathbf{Filt_{vdiag2}} = \boldsymbol{H_{21}} + \boldsymbol{H_{32}}$,
$\mathbf{Filt_{vdiag3}} = \boldsymbol{H_{21}} + \boldsymbol{H_{32}} + \boldsymbol{H_{43}}$.

These filter outputs basically give a measure of signal energies at different directions and scales, the corresponding filtered images are denoted by $F_{Hi}$ , $F_{Vi}$ etc. for $i$=1,2,3 as shown in Fig. 3.

*B. Local energy estimator*

The purpose of the estimator is to transmit the strong bandpass frequency components resulting in a high-constant gray value and weaker frequency components into a low- constant gray value. The most popular magnitude operation | . | is used. One reason for choosing this nonlinear operator is that it is parameter free, meaning it is independent of the dynamic range of the input image and also of the filter amplification. The nonlinear transform is succeeded by a Gaussian low-pass (smoothing) filter of the form

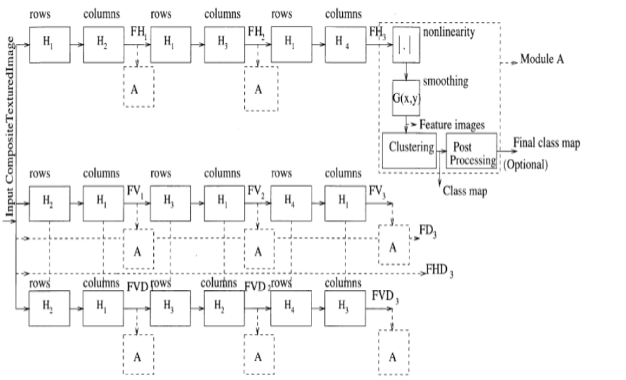



Fig 3. Block diagram of the algorithm used

$$h_G\,(x,y) \;=\; \frac{1}{\sqrt{2\Pi}\sigma} e^{-(1/2\sigma^2)(x^2+\,y^2)} \qquad (8)$$

where, $\sigma$ defines the spatial extent of the averaging filter. Formally, the feature image $Feat_k(x,\ y)$ corresponding to filtered image $F_k(x,y)$ is given by,

$$Feat_k(x,y) \;=\; \textstyle\sum_{(a,b)\epsilon G_{xy}} \Gamma(F_k(a,b)\; h_G\;(x-a,y-b)) \quad (9)$$

where $k$=$H_i$ , $V_i$ etc., $\Gamma(.)$ is the nonlinear function and $G_{xy}$ is a $G$X$G$ window centered at pixel with coordinates ($x$, $y$). The size $G$ of the smoothing or the averaging window in Eq. (9 ) is an important parameter. More reliable measurement of texture feature demands larger window areas. Also, more definite localization of region boundaries requires smaller windows. Another important aspect is that, Gaussian weighted windows are naturally preferable over unweighted windows, as they result in more definite localization of texture boundaries, since averaging blurs the boundaries between textured regions.

*C. Integration of Feature Images*

Let us assume that there are $K$ texture categories $C_1,...C_k$, present in the image. If our texture features are capable of distinguishing these categories then the patterns belonging to each category will form a cluster in the feature space which is compact and different from clusters corresponding to other texture categories. Pattern clustering algorithms are ideal modes for forming such clusters in the feature space. Segmentation algorithm takes a set of features as input and assign a class for each pixel. Fundamentally this can be considered as a multidimensional data clustering problem. Texture segmentation algorithms can be divided into two categories: supervised and unsupervised segmentation [9].

*D. Algorithm*

The texture segmentation algorithm based on $M$-band wavelet decomposition is illustrated in Fig. 3.
This algorithm consist of the following steps:

- The input image is first decomposed into $M$X$M$ channels by wavelet analysis without downsampling. We have used an eight tap 4-band wavelet, so in all we get 16 decomposition channels which means the feature set comprises of 16 feature elements. Out of these 16 features we ignore the low frequency channel feature corresponding to $H_{11}$ and $FHD_1$ and $FVD_1$.
- Since these are nothing but $FH_1$ and $FV_1$, respectively. So only13 features are left.
- These outputs pass through the nonlinear operation followed by smoothing which form the feature images $Feat_k$.
- We get a matrix of size $N$X$M$, where $N$ is the number of feature elements in each vector (13 in this case) and $M$ is the total data size (the total number of pixels in the input image). The features are normalized between [0,1] along each column of the feature matrix and subjected to EM clustering algorithm. This step gives us the class map corresponding to the composite texture image.

## IV. Experimental Results

We have applied our texture segmentation algorithm to several type of texture images along with different clustering algorithms, in order to demonstrate the performance of our algorithm. Table 1 shows the accuracy of our segmentation on fig 4 for different feature extraction techniques applied in combination with various clustering approaches for 10 clusters. The Berkeley dataset [10] has been taken as the benchmark for the experimentation.

| Feature Extraction / Clustering Algorithm | DWT | M-Band | DWP |
|---|---|---|---|
| Kmeans | 66.9 % | 68.4 % | 70.4 % |
| EM | 85.7 % | 92.1 % | 92 % |
| FarthestFirst | 59.9 % | 59.8 % | 62.3 % |
| Manhattan Kmeans | 76.7 % | 78.3 % | 81.8 % |

Fig 4(a). Original image

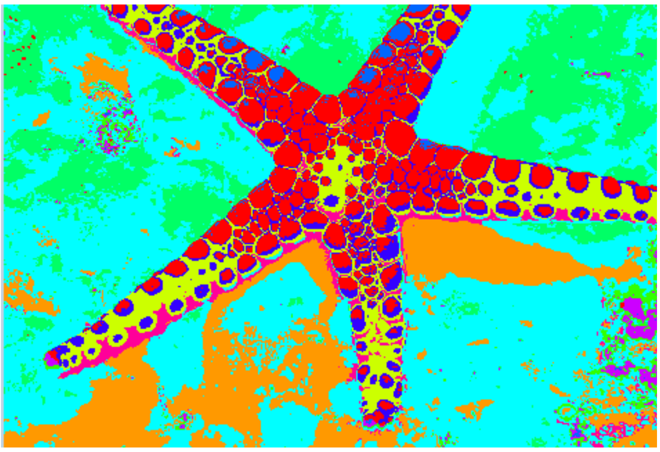
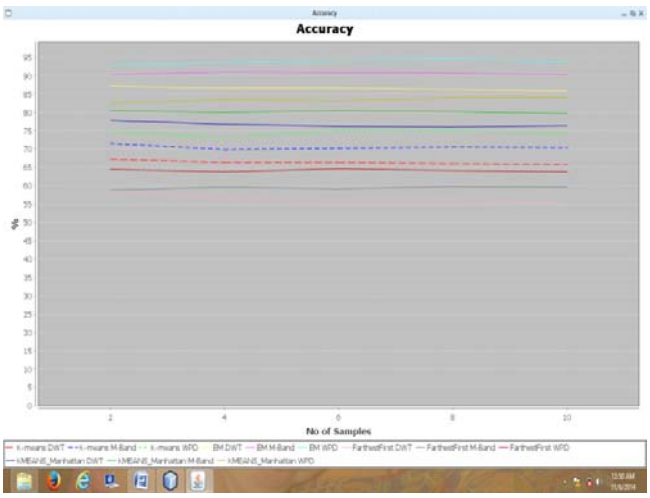


Fig 4(b). Segmentation obtained by the proposed method employing EM and Discrete Wavelet Packet for 10 clusters.

Experiments are performed on 11 images and graph obtained after testing these images on all the above algorithms is shown below.




## V. CONCLUSIONS

In this paper, a new algorithm for adaptive unsupervised segmentation of texture images was presented. The process can be divided in three principal steps: transform, feature extraction and clustering. The transform selected is capable of obtaining details of middle-high frequency, where the most significant information of a texture appears. For clustering, different algorithms like simple Kmeans, Manhattan Kmeans,FarthestFirst and Excitation Maximisation are used. All algorithms were tested on different type of images and the average accuracy obtained with simple Kmeans is 70.65%, with Manhattan Kmeans is 79.18%, with Farthest First is 60.02% and with EM is 91.09%. Experimental results presented prove the efficiency of EM method. Several comparisons with other existing methods in literature are made.

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