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Segmentation of Color Images Using EM Cost with Spatial Refinement Algorithm on MBWT Features

Dr.S.Vasuki[1], G.Veera Senthil Kumar[1] , Dr.L.Ganesan[2]

[1]Department of Electronics and Communication Engineering,
Velammal College of Engineering and Technology, Madurai, Tamil Nadu, India

[2]Department of Computer Science and Engineering,
A.C.College of Engineering & Technology, Karaikudi, TamilNadu, India

***Abstract*— This paper proposes a novel technique to segment the color images combining M-Band Wavelet transform(MBWT) and Expectation Maximization (EM) with cost spatial refinement algorithm. One of the drawbacks of standard wavelets is that they are not suitable for the analysis of high frequency signals with relatively narrow bandwidth. This drawback has been overcome using MBWT. Also M-band wavelet decomposition yields a large number of sub bands which is required for improving the performance accuracy. The proposed algorithm first decomposes the input image into sixteen subimages by applying MBWT. Then, median feature is computed for each subimage and maximum energy subimage is chosen as the appropriate feature space on which EM with cost spatial refinement algorithm is applied. This new combined algorithm produces very good segmentation results by taking advantage of M-Band Wavelet feature extraction and EM with cost spatial refinement algorithm. The segmentation result is more homogeneous and quite consistent with the visualized color distribution in the objects of the original images compared to Fuzzy C means and K means spatial refinement algorithms. Also EM with cost spatial refinement algorithm needs less computational time compared to other clustering algorithms.**

***Keywords*— Color Image Segmentation, M-Band Wavelet transform, EM with cost function, Spatial refinement algorithm, K-Means clustering.**

I. INTRODUCTION

Color image segmentation refers to the partitioning of a multi channel image into meaningful objects. With the growing of digital image databases, efficient segmentation methods are needed for extracting and coding image regions. Color of an image can carry more information when compared to gray levels. In many pattern recognition and computer vision applications, the additional information provided by color can help the image analysis process and yields better results than approaches using only gray scale information. Various approaches to color image segmentation can be classified into several categories: clustering methods, edge based methods, region growing methods and variational methods [1].

Despite the existence of several computing methods, the interest in EM with cost spatial refinement algorithm continues due to its conservation of time. Fuzzy C means and K means spatial refinement algorithms are not adopted because of over segmented result. EM with cost spatial refinement algorithm allows not only grouping objects of an image in clusters but also quite consistent with the visualized color distribution in the objects of the original images.

The wavelet transform is a mathematical tool that can be used to describe the image in multiple resolutions. The wavelet decomposition is a complete representation; since it allows a perfect reconstruction of the original image. The standard discrete wavelet transform(DWT) decimates the wavelet coefficients at each level. Thus, the results of wavelet transform at each level are half the size of the original sequence. The DWT provides the information useful for texture analysis in the image. Its fast implementation is usually performed by using Multiresolution analysis. The wavelet coefficients are sampled based on the Nyquist criteria. The representation is accordingly non-redundant and the total number of sample in the representation is equal to the total number of the image pixels. Orthogonal MBWT is a direct generalization of dyadic orthogonal wavelet transform . Dyadic wavelet transform is not suitable for analysis of high frequency signals, as it decomposes the frequency channel logarithmically but MBWT divides the time-scale space both logarithmically as well as linearly thereby giving better resolution at high frequencies. Also M-band wavelet decomposition yields a large number of sub bands which is required for improving the performance accuracy. M-channel filters decompose the time-scale space into M×M subbands. Human eye shows varying sensitivity response to different spatial frequencies. A Human Visual system divides an image into several bands, than actually visualizing the complete image as a whole. This fact motivated us to use the M-band filters which are essentially frequency and direction oriented band pass filters.

The objective of the work is to segment color images using EM with cost spatial refinement algorithm on M-Band and wavelet features. In the first stage, features are extracted by the decomposition of color image into sixteen subimages. Maximum information subimage is derived by computing the median feature on which EM with cost spatial refinement technique is applied to obtain the final segmented output. In comparison with the direct application of EM with cost spatial refinement technique, MBWT based EM with cost spatial refinement technique is superior for texture based segmentation.

An overview of this paper is as follows. In section 2, the analysis of MBWT is discussed. In section 3, the procedure for image segmentation using EM with cost spatial refinement algorithm is explained. In section 4, the proposed methodology is explained with flowchart. In section 5, experimental results and in section 6, performance evaluations are discussed. The conclusion is given in section 7.

II.M-BAND WAVELET TRANSFORM

The standard wavelets are not suitable for the analysis of high frequency signals with relatively narrow bandwidth. A possible solution to this is to use an over complete wavelet decomposition called M-Band Wavelet Transform(MBWT).M-band wavelet decomposition yields a large number of sub bands which is required for improving the performance accuracy. Unlike the standard wavelet decomposition which gives a logarithmic frequency resolution, the M-band decomposition gives a mixture of a logarithmic and linear frequency resolution. The basic idea is simple. For M=4, the filter bank is shown in Fig.1.

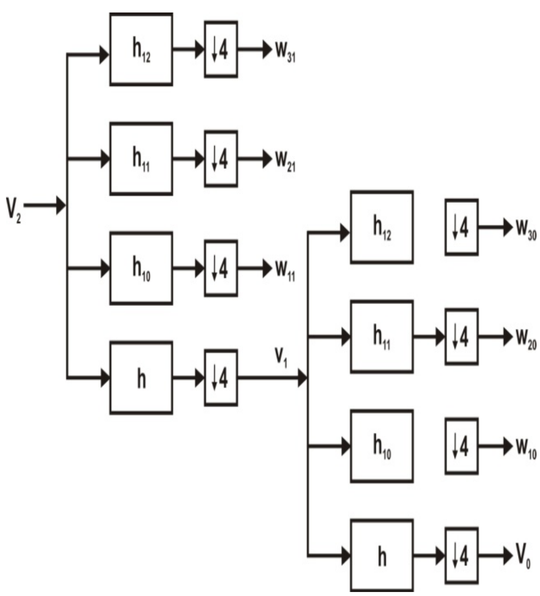

Fig.1. Channel filter bank for M=4

The filter bank in essence is a set of band pass filters with frequency and orientation selective properties. The filtering stage consists of orthogonal and linear phase M band wavelet filters. These filters have Perfect Reconstruction with Quadrature Mirror Filter (PR-QMF) structure and are symmetrical. Intuitively, for good edge boundary localization, it is desirable to have a filter with compact spatial domain representation while for reliable discrimination of different texture frequency contents the filter should have a good frequency response localization and high stop band attenuation. Also symmetry of the filter responses is an important factor. A non-symmetric filter response consistently leads to edge detection error and consequently higher classification error.

Here, 4^2-channel is developed through 2D separable transform by the tensor product of 4-band 1D wavelet filters but without any sub sampling. The $[x,\ y]^{th}$ resolution cell is obtained via the filtering steps,

$$H_{11} = H_1(\omega_x) H_1(\omega_y) \quad \ldots(1)$$

$$H_{m_x m_y} = H_{m_x}(\omega_x) H_{m_y}(\omega_y) \quad \ldots(2)$$

for $m_x=m_y=2,3$and 4.
where, H denotes the transfer function of a filter. The decomposition of the image into 4×4 = 16 channels is illustrated in Fig.2(a).

A typical edge detection filter corresponding to a particular direction covers a certain region in the 2D spatial frequency domain. This is illustrated in Fig.2(b), where f_x and f_y are the horizontal and vertical frequencies respectively.

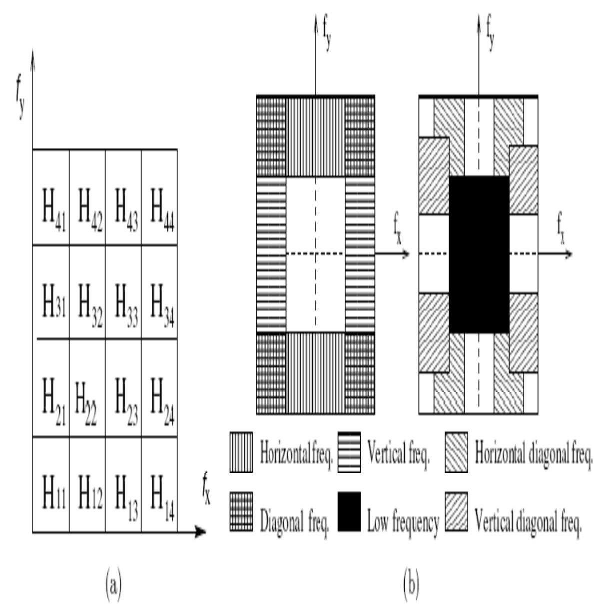

Fig.2. Decomposition of 4 Band Wavelet Transform
(a) Frequency Bands Corresponding to Decomposition Filters
(b) Frequency Vector Representation for Filtering

These filter responses basically give a measure of signal energies at different directions and scales, the corresponding filtered images are denoted by F_{diagj}, F_{hdiagj} and F_{vdiagj} for j=1;2;3 as shown in Fig.3.

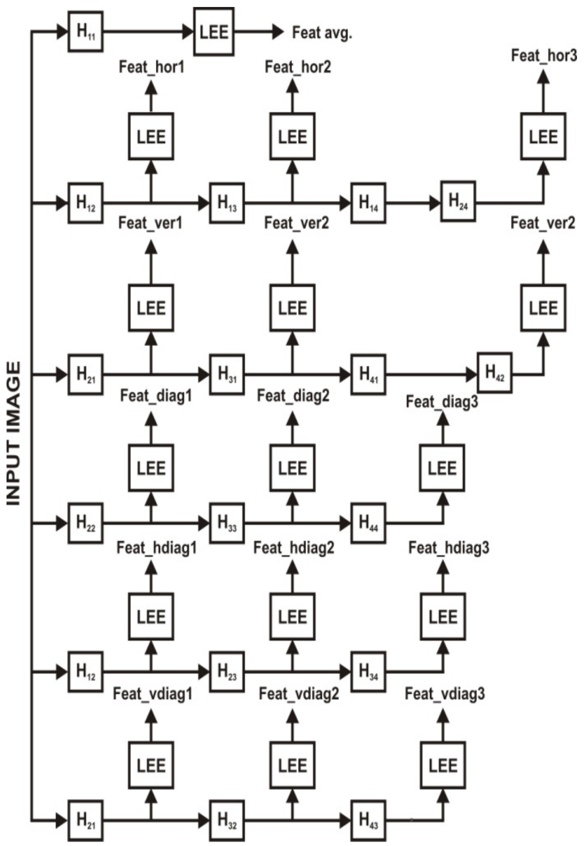

Fig.3. Feature Extraction Process Using MBWT

III. EM CLUSTERING WITH COST FUNCTION

The EM algorithm is a general method of finding the maximum-likelihood estimate of the parameters of an underlying distribution from a given observable data set X when the data is incomplete or has missing values.For existing complete data set, it is assumed the joint density function :

$$f(z|\Theta) = p(x, y|\Theta) = f(y|x,\Theta)\, p(x|\Theta) \quad \ldots(3)$$

In the cases (e.g., missing data values in samples of a distribution), it is assumed to have a joint relationship between the missing and observed values. With this new density function, a new likelihood function can be defined as,

$$L(Z|\Theta) = L(X,Y|\Theta) = p(X,Y|\Theta) \quad \ldots(4)$$

Note that this function is in fact a random variable since the missing information is unknown, random, and presumably governed by an underlying distribution.

The complete log likehood (i.e. the one from which Θ is estimated if the complete $Z=\{X,Y\}$ is observed) becomes

$$\log L(Z|\Theta)=\log L(X,Y|\Theta)=\log p(X,Y|\Theta)=\sum_{i=1}^{N}\sum_{k=1}^{K} y_i^k \log[\alpha_k G(x_i|\theta_k)] \quad \ldots(5)$$

The EM algorithm produces a sequence of estimates $\{\Theta^{(t)} : t = 0,1,2,\ldots\}$ by alternatively applying two steps until some convergence criterion is met.

A. Expectation step

The EM algorithm first finds the expected value of the complete log-likehood $\log L(X,Y|\Theta)$ with respect to the missing data Y given the observed data X and the current parameter estimates. That is, the so called Q-function is defined as:

$$Q(\Theta,\Theta^{(t)}) \equiv E[\log p(X,Y|\Theta)\,|\,X,\Theta^{(t)}] = \log p(X,W|\Theta) \quad \ldots(6)$$

where $W = E[Y\,|\,X,\Theta^{(t)}]$ and $\Theta^{(t)}$ are the current parameters estimates that are used to evaluate the expectation and Θ are the new parameters that is optimized to increase Θ.

Here the first argument Θ corresponds to the parameters that ultimately will be optimized in an attempt to maximize the likelihood. The second argument $\Theta^{(t)}$ corresponds to the parameters that is used to evaluate the expectation. The evaluation of this expectation is called the E-step of the algorithm.

B. Maximization step

The M-step of the EM algorithm is to maximize the expectation that is computed in the E-step. ie.,

$$\Theta^{(t+1)} = \arg\max_{\Theta} Q(\Theta,\Theta^{(t)}) \quad \ldots(7)$$

The M-Step consists of the following computations:

The new mixture weights:

$$\alpha_k^{(t+1)} = \frac{1}{N}\sum_{i=1}^{N} p_{ki}^{(t)}, \quad 1 \le k \le K. \quad \ldots(8)$$

The updated means are calculated:

$$\bar{\mu}_k^{(t+1)} = \left(\frac{1}{\sum_{i=1}^{N} p_{ki}^{(t)}}\right)\sum_{i} p_{ki}^{(t)}.x_i, \quad 1\le k\le K \quad \ldots(9)$$

The updated covariance are calculated:

$$\Sigma_k^{(t+1)} = \left(\frac{1}{\sum_{i=1}^{N} p_{ki}^{(t)}}\right)\sum_{i=1}^{N} p_{ki}^{(t)}.(x_i - \bar{\mu}_k^{(t+1)})^T, \quad 1\le k\le K. \quad ..(10)$$

After the computation of all the new parameters, the membership weights in the E-step are recomputed, and hence the parameters again in the E-step, and updating the parameters is continued in this manner. Hence, the EM algorithm is an iterative scheme that guarantees a local maximum of the likelihood of the data.

EM algorithm doesn’t consider the pixel neighborhood for clustering [4]. The segmentation results can be improved, by considering the neighborhood effects. For

considering neighborhood effects, cost function with Mahalanobis distance is used. Mahalanobis distance is based on correlations between the variables by which different patterns can be identified and analyzed. Cost function measures the cost of giving the label to a particular pixel.
The cost function C is defined as follows:

$$C(x_i, l) = \lambda_p Dist(x_i, \theta_l) + \lambda_n V(x_i) \quad \ldots(11)$$

$$V(x_i) = \sum_{s=1}^{N_B} V(x_i, s) \quad \ldots(12)$$

$$V(x_i, s) = \sum_{x_{j,k} \varepsilon \aleph} \frac{\Delta(x_{i,s}, x_{j,k})}{\bar{\aleph}} \quad \ldots(13)$$

$$\Delta(x_{i,s}, x_{j,k}) = \begin{cases} +\dfrac{1}{|k-s|+1} if l_i = l_j \\ -\dfrac{1}{|k-s|+1} if l_i \neq l_j \end{cases} \quad \ldots(14)$$

Mahalanobis distance is defined as,

$$Dist(x_i, \theta_l) = (x_i - \mu_l)^T \varepsilon_l^{-1} (x_i - \mu_l) \quad \ldots(15)$$

Fig.4. depicts the complete process involved in EM algorithm with cost function.

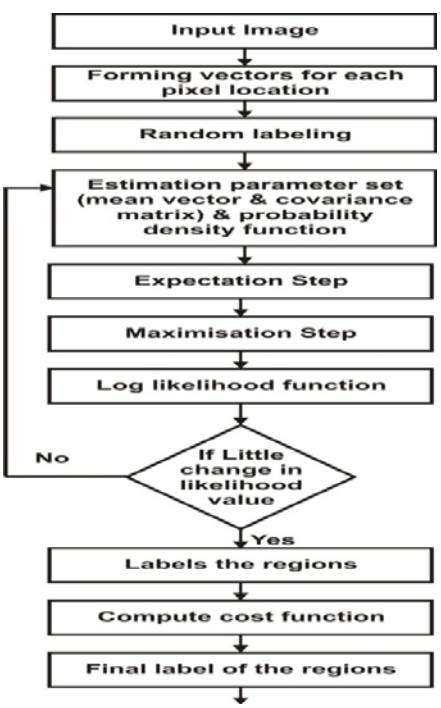

Fig.4. EM Clustering with Cost Function

IV. EM WITH COST SPATIAL REFINEMENT ALGORITHM

In this work, K-means clustering, agglomerative hierarchical clustering and probabilistic clustering are combined by introducing spatial refinement concept, to take advantage of the characteristics of these three clustering methods and eliminate their potential limitations. Spatial refinement can work with a complex and large dataset, including small objects and outliers. The steps involved in EM with cost spatial refinement algorithm are shown in Fig.5.

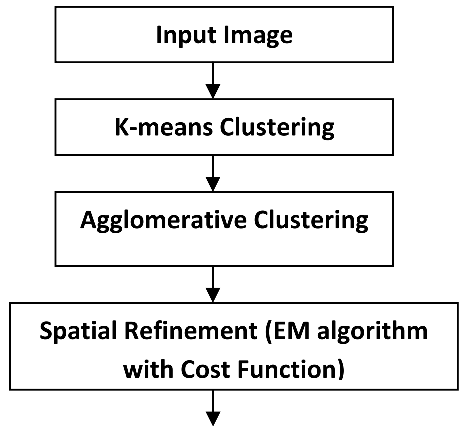

Fig.5. EM with Cost Spatial Refinement Algorithm

In the proposed segmentation algorithm, k-means clustering is used as the initial step, to obtain the segmentation results for high number of clusters. Here, high number of clusters is set to be ten. Hence, the output from the k-means clustering is the labeled image consisting of ten clusters.

Agglomerative Hierarchical Clustering(AHC) yields a hierarchical structure of clusters, representing how cluster pairs are joined. In principle, the algorithm starts with assigning each pixel to individual clusters. At each iterative step, the proximity matrix is calculated for all cluster pairs and the two ‘closest’ pair clusters are merged. The process will continue until there is only one cluster. Depending on the definition of a distance between clusters, AHC are variants of single linkage, complete linkage, average linkage and Ward’s algorithms [5].

In this work, agglomerative hierarchical clustering with Ward’s distance measure is used. The distance in Ward’s method is defined as the squared Euclidean distance of the cluster mean vectors. Hence, Ward’s method is related to K-means through the minimum-variance criterion. A dendrogram is produced, representing nested clusters and the similarity levels at which clusters are joined. The dendrogram can be cut at several levels in order to obtain an arbitrary number of clusters. It circumvents the problem of the pre defined number of K clusters in K-means clustering algorithms. By starting with assigning each pixel to individual clusters the algorithm is not sensitive to outliers. Outliers will be kept in separate clusters, not influencing the other clusters. Overall, agglomerative hierarchical clustering scheme considers only clusters that are obtained in the previous step.

Determining the number of clusters is a difficult problem in all clustering algorithms. Milligan and Cooper (1985) [11] developed some measures of spread within and between clusters. The within cluster inertia, *W*, is defined as variation of individual points to their center and the between cluster inertia, *B*, is defined as the variation of cluster centers around the overall mean.

$$W = \frac{1}{N}\sum_{K}\sum_{i \in C_k} d(x_i, c_k) \qquad \dots (16)$$

$$B = \frac{1}{N}\sum_{K} n_k d(c_k, c) \qquad \dots (17)$$

In clustering algorithms, minimizing the sum of squares criterion would thus minimize *W*. The number of optimum clusters is found out by, the ratio of within to between cluster inertia and it is given by

$$I = \frac{W}{B} \qquad \dots (18)$$

For each merging stage, this index value is found out. A graph is drawn between these index values and the number of clusters, from which the optimum number of clusters for the input image is obtained by the position of sudden change in the graph.

Spatial refinement is accomplished using EM algorithm with cost function on the initially clustered output with optimum number of clusters derived from agglomerative clustering. The distance of each pixel with the centroids is calculated and the pixels are reassigned to the 'closest' adjacent clusters. This refinement process iterates until there is no change in the pixel classification and reallocates misassigned points using the information of points in the spatial domain.

The concept of spatial refinement is illustrated in Fig.6. It alleviates the inflexibility of agglomerative hierarchical clustering. By limiting the refinement only to boundary points, the clustering is expected to have a high continuity. At any iteration, let x_i be point in cluster S_c but not a border point. Even if there exists a cluster *d* such that $d(x_i, c_d) < d(x_i, c_c)$ then x_i is not considered to be re assigned to cluster *d*. It will only be joined to cluster *d* when it is at the boundary of cluster *c*. Therefore, spatial refinement is fast, since only a limited number of reallocations have to be considered.

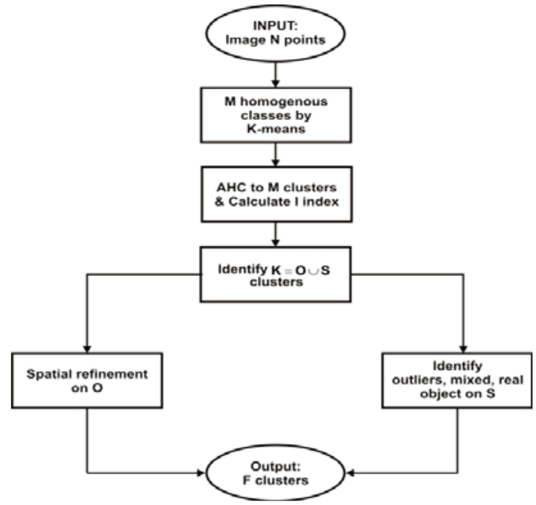

Fig.6. Spatial Refinement Process

V. EXPERIMENT RESULTS

The performance of the MBWT based EM clustering with cost spatial refinement algorithm is tested on a variety of natural color images. Fig.7 shows the comparison of segmentation results of the proposed method with MBWT based K-Means spatial refinement and Fuzzy C-Means spatial refinement technique. It depicts the superiority of the proposed frame work over the application of K-Means and Fuzzy C-Means clustering algorithms. It is observed that Fuzzy C means spatial refinement clustering algorithm does not produce good segmentation results for all kind of images. Almost over segmented images are obtained compared to other two algorithms. K-means spatial refinement algorithm produces better segmentation results for smooth textured images. But it is not superior to EM with cost spatial refinement algorithm. Specifically, in "HP2" image, eventhough, the three regions are correctly identified, Fuzzy C means does not separate the regions effectively whereas K-means produces inhomogeneous regions. Even in "Delta" image, two colors are enough to express the shape, material and its background. Our proposed method captures the two regions correctly and produces uniform segmentation output. In brief, the experimental results of MBWT based EM with cost spatial refinement algorithm are quite consistent with the visualized color distribution in the objects of the original images.

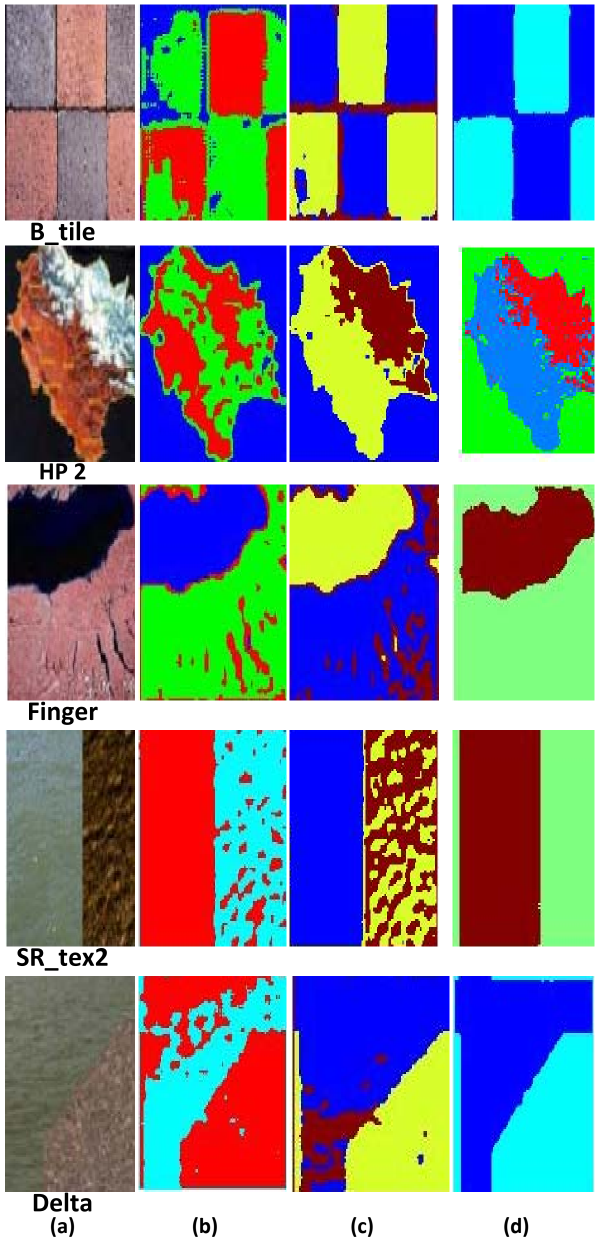

Fig.7. Segmentation Results Using MBWT Features
a)Input images b) Segmented images using Fuzzy C-Means Spatial Refinement c) Segmented images using K-Means Spatial Refinement d) Segmented images using EM with Cost Spatial Refinement

VI. PERFORMANCE EVALUATION

To evaluate the segmentation results of real images as well as synthesized ones, suitable evaluation measures are developed and used in this work. The performance of the proposed segmentation algorithm is analysed by the measures:

Deviation ratio $$D_r = \frac{N_{MS}}{N_{Tot}} \quad ...(19)$$

where N_{MS} – Number of misclassified pixels
N_{Tot} – Total number of pixels

Average dispersion degree $$A_D = \frac{1}{N_{Tot}} \sum_{c=1}^{k} B_c \quad ...(20)$$

where k – number of clusters, B_c – number of boundary points on cluster c.

From the results it is observed that MBWT features are well suited for segmenting the highly textured images, because of its high discrimination characteristics on boundaries and hence the dispersion degree of the cluster is lower. And also, most of the pixels are correctly classified in turn the deviation ratio is smaller.

Table 1 elaborates the values of the evaluation measures for RGB color space which produces very best results as well as the regions and boundaries are correctly identified which influences smaller deviation ratio and smaller average dispersion degree.

TABLE 1
Performance Measures of M-Band Wavelet based EM with cost spatial refinement in Color Models.

Input	R	A_D	D_r
B_tile	2	0.0916	0.4595
HP 2	3	0.0561	0.1357
Finger	2	0.1158	0.0944
SR_tex2	2	0.1140	0.0618
Delta	2	0.0816	0.0372

VII. CONCLUSION

In this paper, we propose a new approach to color image segmentation. First, MBWT is applied on the input color image and energy is computed for the resultant sub images. Then, maximum energy sub image is selected on which EM Clustering with cost spatial refinement technique is applied. This is very helpful in recognizing the objects of a color image. The output regions of the color segmentation tend to distinguish different objects in a color image. The quality of segmentation is better compared to K-Means and Fuzzy C-Means spatial refinement technique. The proposed approach can be applied for a variety of images like multi spectral and medical images.

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