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Studies on Colour Image Segmentation Method Based on Finite Left Truncated Bivariate Gaussian Mixture Model with K-Means

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Abstract

Colour Image segmentation is one of the prime requisites for computer vision and analysis.Much work has been reported in literature regarding colour image segmentation under HSI colour space and Gaussian mixture model (GMM). Since the Hue and Saturation values of the pixel in the image are non-negative. And may not be meso-kurtic, it is needed left truncate the Gaussian variate and is used to represent these two features of the colour image. The effect of truncation can not be ignored in developing the model based colour image segmentation. Hence in this paper a left truncated bivariate Gaussian mixture model is utilized to segment the colour image. The correlation between Hue and Saturation plays a predominant role in segmenting the colour images which is observed through experimental results. The expectation maximization (EM) algorithm is used for estimating model parameters. The number of image segments can be initialization of the model parameters are done with K-means algorithm. The performance of the proposed algorithm is studied by calculating the segmentation performance techniques like probabilistic rand index (PRI), global consistency error (GCE) and variation of information (VOI). The utility of the estimated joint probability density function of feature vector of the image is demonstrated through image retrievals. The image quality measures obtained for six images taken from Berkeley image dataset reveals that the proposed algorithm outperforms the existing algorithms in image segmentation and retrievals.

Index terms — Image Segmentation, Hue, Saturation, Finite Left Truncated Bivariate Gaussian distribution, K-means algorithm, Image Quality Metrics, EM- algorithm.

groups. It is an important technology for image processing and understanding. The structural characteristics of objects and surfaces in an image can be determined by segmenting the image using image domain properties. One of the major advantages of image segmentation is denoising. Denoising is the process of removing unwanted noise from the image. Segmentation specifically attempts to separate structure from noise on a local scale. It is one of the most important steps in computer vision and analysis.

For the last three decades lot of work has been reported in literature regarding image segmentation methods (Lucchese L. et al (2001), Srinivas Y. and Srinivas ??ao K. (2007), Majid Fakheri et al (2010), Siddhartha Bhattacharyya (2011)). The image segmentation methods can be divided into two categories depending upon the type of image. The images can be broadly categorized into two types namely, gray level images and colour images. A gray level image is usually characterized by pixel intensity (Farag A..A.. et al (2004), Seshashayee M. et al (2011), Srinivas Yerramalle et al (2010)). But in colour images the colour is a perceptual phenomenon related to human response to different wavelengths in the visible electro-magnetic spectrum. In colour images the features that represent the image pixel are highly influenced by three feature descriptions namely, intensity, colour and texture. Among these features colour is the most important one in segmenting the colour images since intensity and texture features also be embedded in colour features. (Fesharaki and Hellestrand (1992), Kato Z. et al (2006), Kang Feng et al (2009), Kaikuo Xu et al (2011)). A better colour space than the RGB space in representing the colours of human perception is the HSI space, in which the colour information is represented by Hue and Saturation values. Thus the human perception of image can be characterized through a bivariate random variable consisting of Hue and Saturation which can be measured using generic structure of a colour appearance model (Sangwine et al (1998)). Ferri and Vidal (1992), Lee E. et al(2010), Dipti P. and Mridula J. (2011) and others have reviewed colour image segmentation techniques. Among these mage segmentation is a process of extracting useful information from the images through features and dividing the whole image into various homogeneous groups in which, the pixels within the group are more homogeneous and are heterogeneous between the I model based image segmentation methods are more efficient than the edge based or threshold or region based methods (Lucchese L. et al (2001)). In model based image segmentation the whole image is divided into different image regions and each image region is characterized by a suitable probability distribution. For ascribing a probability model to the feature vector of the pixels in the image region, it is needed to study the statistical characteristics of the feature vector.

In image segmentation it is customary to consider that the whole image is characterized by a finite Gaussian mixture model. That is, the feature vector of each image region follows a Gaussian distribution (Haralick and Shapiro (1985) **??**010)). The image segmentation methods based on Gaussian mixture model work well only when the feature vector of the pixels are having infinite range and the distribution of the feature vector is symmetric and meso-kurtic. But in many colour images the feature vector represented by Hue and Saturation are having finite values (say nonnegative) and may not be mesokurtic and symmetric. Hence, to have an accurate image segmentation of these sorts of colour images it is needed to develop and analyze image segmentation methods based on truncated bivariate mixture distributions.

Here, it is assumed that the feature vector in different image regions follows a left truncated bivariate Gaussian distribution and the feature vector of the whole image is characterized by a finite left truncated bivariate Gaussian mixture model. This assumption is made since the Hue and Saturation values of the pixel which represents the bivariate feature vector can take nonnegative values only. Hence, the range of the Hue and Saturation values are to be left truncated at zero. The effect of the truncated nature of Hue and Saturation cannot be ignored, since the leftover probability is significantly higher than zero in the left tail end of the distribution. This left truncated nature of the bivariate feature vector can approximate the pixels of the colour image more close to the reality.

In this method of segmentation, the number of image regions is obtained by Using the estimated joint probability density functions of the feature vector of pixels of each image, the images are retrieved. The efficiency of the developed algorithm in image retrieval is also studied by computing the image quality metrics like maximum distance, image fidelity, mean square error, signal to noise ratio and image quality index and the results are presented. A comparative study of these quality measures with those obtained from the Gaussian mixture model with K-means revealed that this algorithm performs better.

1 II. FINITE LEFT TRUNCATED BIVARIATE GAUSSIAN MIXTURE MODEL

The effect of truncation in bivariate Gaussian distribution has been discussed by several researchers (Norman L.Johnson, Samuel Kotz and Balakrishnan (1994)). The probability density function of the left truncated Gaussian distribution (truncated at zero) is,0 0 ; (,) (, ;) , 0 0 (,) x y f x y g x y f x y dxdy ? ? ? < < < < ? ? = ? ? (1)

Where, zero is the truncation point for both the Hue and saturation, (,) f x y is the probability density function of the bivariate Normal distribution is2 2 1 1 2 2 2 2 1 1 2 2 1 2 1 1 2 1 (,) exp 2(1) 2 x x y y f x y µ µ µ µ ? = ? + ? ? 1 2 1 1 < < + ; < y < + , 0 ; 0 ; < < , x ? ? ? ? ? ? ? ? > > ? ? ? 1 2 < < + ; < < + µ µ ? ? ? ? ? ?

The value of0 0 1 (,) f x y dxdy ? ? ? ? ? ? ? ? ? ? ? is significant

based on the values of the parameters. This distribution includes the skewed, asymmetric bivariate distributions as particular cases for limiting and specific values of the parameters. The various shapes of the frequency curves of the left truncated bivariate Gaussian distribution are shown in Figure1.

Fig1 : Shapes of left truncated bivariate Gaussian frequency surfaces

Following the heuristic arguments given by Bengt Muthen (1990), the mean value of 'X'(hue) is obtained asE(X) = 1 µ + 1 ? A**(3)**

Where,1 1 1 2 1 2 A = 1 1 1 1 1 2 1 2 c c µ µ µ µ µ µ ? ? ?? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? + ?

and c = ( )1/ 2 2 1 ? ? ?

, ? , ? are the ordinate and area of standard Normal distribution. Similarly the mean value 'Y'(saturation) isE(Y) = 2 µ + 2 ? B (4) Where, 2 2 2 1 2 1 2 2 1 2 1 B = 1 1 2 c c µ µ µ µ µ µ ? ? ?? ? ? ? ? ? ? ? ? ? ?? + ?

and c is as given in equation (3)

The Variance of X isV(X) = 2 1 ? R -2A 1 ? A +A 2 = 2 1 ? R -A 2 (2 1 ? -1)**(5)**

Where,2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 - - - - - - - - R ( ) ( ) 1 ( ) -( ) ( ) ( ) 1 ( ) -( ) c c µ µ µ µ µ µ µ µ ? ? ?

? = + ? ? + ? 1 1 1 1 1 1 1 - - - ( ) ( ) -( ) , c c µ µ µ ?? ?

and c and A is given in equation .

(3) The Variance of Y isV(Y) = 2 2 ? T -2B 2 ? B +B 2 = 2 2 ? T -B 2 (2 2 ? -1) (6) Where, 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 - - - - - - - - T ( ) ( ) 1 ( ) -( ) ( ) ( ) 1 ( ) -( ) c c µ µ µ µ µ µ µ µ ? = + ? ? + ? 1 2 2 2 2 2 2 - - - ( ) ( ) -( ) , c c µ µ µ ?? ?

c and B are as given in equations (3) and (**??**)

respectively. The Covariance of (X, Y) isCOV (X, Y) = 1 2 U ? ? -AB (1 ? + 2 ? -1)**(7)**

where,1 1 1 2 1 1 2 1 1 1 2 1 1 2 1 - - - - - - - U ( ) ( )1 ( ) -( ) ( ) ( ) -( ) c c c µ µ µ µ µ µ µ ?? = + ?? 2 2 1 2 2 2 1 2 - - - - ( ) ( ) 1 ( ) -( ) , c µ µ µ µ ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? + ?? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ?

c, A and B are as given in equations (3) and (**??**) respectively.

Since the entire image is a collection of regions, which are characterized by left truncated bivariate normal distribution, it can be characterized through a K-Component finite left truncated bivariate Gaussian distribution and its probability density function is of the form 1 (,) (, ;)K i i i i i h x y g x y ? ? = = ?**(8)**

Where, K is the number of regions, i ? >0 are weights such that1 1 K i i ? = = ? and { } 2 2 1 2 1 2

= , , , ,i i i i i

? µ µ ? ? ? is the set of parameters. (, /)i i i i

g x y ? given in equation (1) represent the probability density function of the i th image region. i ? is the probability of occurrence of the i th component of the finite left truncated bivariate Gaussian mixture model (FLTBGMM) i.e., the probability that the feature belongs to the i th image region.

The mean vector representing the entire image isT ( ) 1 (W) ( ) 1 K E X i i i E K E Y i i i ? ? ? ? ? ? ? = ? ? = ? ? ? ? ? = ? ?**(9)**

Where, ( ) L (?) = 1 (, ;) N s s s h x y ? = ? = 1 1 ((, ;)) N K i i s s s i g x y ? ? = = ? ? (10) ( ) 2 2 1 1 2 2 2 1 1 2 2 1 1 2 1 2 0 0 1 2 exp 2 (1) 2 1 , ; N s i s i s i s i i i i i i i s i i i i i K x x y y i f x y dxdy µ µ µ µ ? ? ? ? ? ? ? ? ? ? ? ? ? ? = = ? + ? = ? ? ? ? ? ? ? ? ? ? ? ? ? ? This implies log L (?) = 1 1 log((, ;)) s s N K g x y i i s i ? ? ? ? = =**(11)**

The updated equations of EM-algorithm for estimating the model parameters are

) **??** ;)N l l k k s s s t x y N ? ? + = ? ? = ? ? ? ( )**( ) ( ) ( ) 1 1 (, ;) 1 (**l l k k s s K l l s k i s s i N g x y N g x y ? ? ? ? = = ? ? ? ? ? = ? ? ? ? ? ? ? ?**(12) Where, ( ) (, ;**

)l k s s

g x y ? is as given in equation (1).

For updating 1k µ we have,( ) ( ) (1) ( ) ( ) ( ) ( ) ( ) 2 1 1 ( ) 1 1 1 2 ( ) (, ;) (, ;) (, ;) A B 0 l l N N N l l l l l l k s k k k s s k s s s k s s k k l s s s k y t x y t x y x t x y ? ? ? µ µ ? ? ? + = = = ? ? ? ? ? ? + + ? = ? ? ? ? ? ? ? ? ? ? ? (13)

Similarly for updating 2k µ , we have ,( ) ( ) (1) ( ) ( ) ( ) ( ) ( ) 1 2 2 ( ) 1 1 1 1 ( ) (, ;) (, ;) (, ;) B A 0 l l N N N l l l l l l k s k k k s s k s s s k s s k k l s s s k x t x y t x y y t x y ? ? ? ? µ µ ? ? ? + = = = ? ? ? ? ? ? + + ? = ? ? ? ? ? ? ? ? ? ? ? ? (14)

Where,( ) ( ) ( ) ( ) ( ) ( ) ( ) ( ) ( ) ( ) ( ) ( ) ( )**1**

, ; , ; , ; , ; , ;l l l l k k s s k k s s l k s s K l l l s s i i s s i g x y g x y ? ? ? ? ? ? = = = ? , ( ) 2 2 1 1 2 2 2 1 1 2 2 ( ) 2 1 2 0 0 1 exp 2 2(1) (, ;) = 2 1 , ; s k s k s k s k k k k k k k l k s s k k k k x x y y g x y f x y dxdy ? ? µ µ µ ? ? ? ? ? ? ?? + ?

A and B are as given in equations (3) and (**??**) respectively. The updated equations for 2 1k ? at (1) l + th iteration is, ( ) 2 (1) ( ) 1 2 2 ( ) (1) 1 1 ( ) 1 ( ) ( ) ( )( ) (, ;) + 0 k k l k l l k k l s s s k s s l s k l k N l l k x x y t x y D E ? µ ? µ µ ? ? ? ? + + = ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ?? ? = ? ? ? ? ? ? ? ? ? ? ? ? ?**(15)**

Where, ( ) **??** , ;)k s s l t x y ?

is given in equation (**??**4), ( )1 1 1 1 1 2 1 2 1 1 1 2 1 1 1 2 1 1 1 1 - - - ( ) -( ) - - - 1 (-) 1 ( ) -( ) , k k k k k k k k k k k k k k k k k k k k k k k D c c c µ µ µ ?? ? ? ? ? ? ? ? ? ? ? ? µ µ µ ? ? µ ? ? ? ? ? ? ? = + + + ?

And1 2 1 2 1 1 2 1 1 2 1 2 1 2 1 2 2 1 2 - - - ( ) -) - - - (-) 1 ( ) -( ) k k k k k k k k k k k k k k k k k k k k k k k E c c k c µ µ µ ? ?? ? ? ? ? ? ? ? ? ? ? µ µ µ ? ? µ ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? = + ? + ? ( ) 1 2 1 2 1 1 2 1 - - - + - 1 ( ) -( ) k k k k k k k k k k c µ µ µ ? ? µ ?

The updated equations for 2 2k ? at (1) l **??** , ;) **??** , ;)+ th iteration is 1 ( ) 2 ( ) (1) 1 2 2 ( )**(1) 1 2 ( ) 1 ( ) ( ) ( )**( )+ 0 k k l k l l k k l s s s k s s l s k l k N l l k y x y t x y G E ? µ ? µ µ ? ? ? ? + + = ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? = ? ? ? ? ? ? ? ? ? ? ? ? ? ?**(16) ( )**k s s l t x y ?

and E are as given in equations (**??**4) and (15) respectively and Therefore the updated equation for estimating k? is ( ) ( ) ( ) ( ) 2 2 1 2 2 2 1 2 2 2 1 2 2 2 2 2 2**2 1 2 ( ) 1 1 1 (1 1 1 (, ;) = ()**) 0 1 k s k s k k s s k k k k s k s k k k k k k k N l x y t x y s x y D F E ? ? µ µ ? ? ? ? µ µ ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? + ?? ? + ? ? + + ? + + = ? ? ?? ? ? ? ? ? ? ? ? ? ?? ? ? ? ?**(17)**

Where, ( ) (, ;

)k s s l t x y ?

, D, E and G are as given in equations (**??**4) ,(15) and (16) respectively and .

where, ( )2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2**1 2 1 1 ( ) - ( ) 2 1 (-) ( ) - ( ) , - - - -**- - 1 k k k k k k k k k k k k k k k k k k c c k k c k k G ?? ? ? ? ? ? ? ? ? ? ? ? ? µ µ µ ? ? ? µ µ µ µ ? ? ? ? ? ? = + ? ? ? ? ? ? + + ? 2011 October ( ) 2 2 2 2 1 2 2 2 2 1 2 - - - ( ) 1 ( ) -( ) k k k k k k k k k k k c µ µ µ ? ? µ ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? + ? + 1 2 2 2 2 2 2 - - - ( ) ( ) -( ) k k k k k k k k k c c µ µ µ ?

Solving equations (12), (**??**3), (**??**4), (15), (16) and (17 **??**000)). This method performs well, if the sample size is large, and the computation time is heavily increased. When the sample size is small, some small regions may not be sampled. To overcome this problem, we use K-means algorithm to divide the whole image into various homogeneous regions. In K-means algorithm the centroids of the clusters are recomputed as soon as pixel joins the cluster. The initial values of i ? can be taken asi ? = K 1

, where, K is the number of image regions obtained from the K-means algorithm (Rose H. Turi (2001)). K-means algorithm uses an iterative procedure that minimizes the sum of distances from each object to its cluster centroid, over all clusters. This procedure consists of the following steps.

1) Randomly choose K data points from the whole dataset as initial clusters. These data points represent initial cluster centroids. 2) Calculate Euclidean distance of each data point from each cluster centre and assign the data points to its nearest cluster centre. 3) Calculate new cluster centre so that squared error distance of each cluster should be minimum. 4) Repeat step 2 and 3 until clustering centers do not change. 5) Stop the process.

The efficiency of the EM-algorithm in estimating the parameters is heavily dependent on the number of regions in the image. The number of mixture components taken for K-means algorithm is obtained,

2 IV. INITIALIZATION OF PARAMETERS BY K-

3 MEANS

In the above algorithm, the cluster centers are only updated once all points have been allocated to their closed cluster centre. The advantage of K -means are that it is a very simple method, and it is based on intuition about the nature of a cluster, which is that the within cluster error should be as small as possible. The disadvantage of this method is that the number of clusters must be supplied as a parameter, leading to the user having to decide what the best number of clusters for the image is **??** ? for each image region and with the method of moments given by Bengt Muthen (1990) for Truncated Bivariate Normal Distribution with initial parameters as? i = 1/K for i=1,2,?,K 1k µ = 1k

x is the k th region sample mean of the Hue angle. Substituting these values as the initial estimates, we obtain the refined estimates of the parameters by using the EM-algorithm.

V.

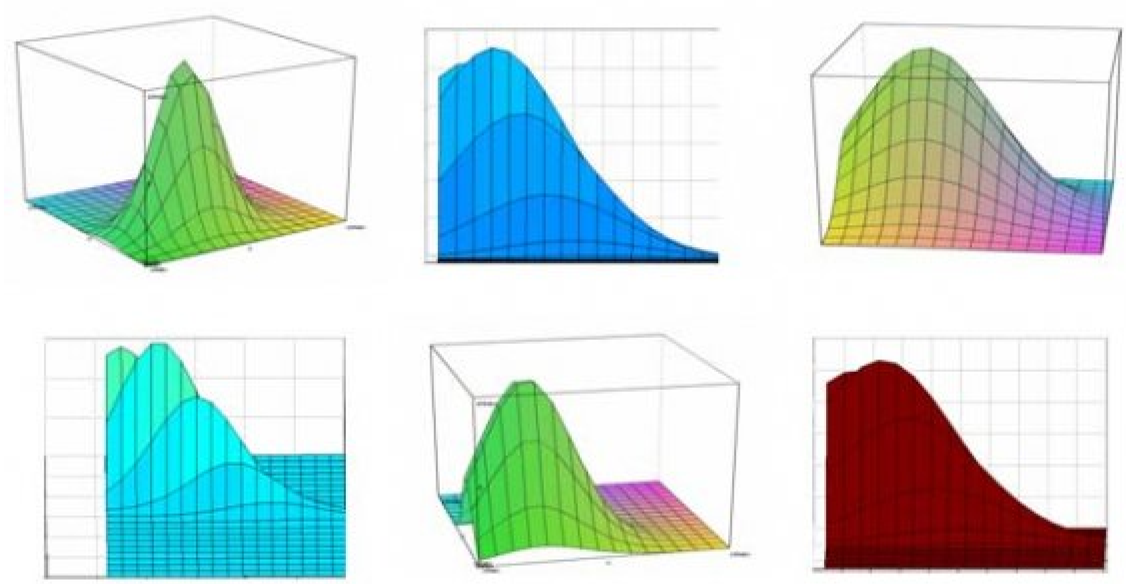
4 SEGMENTATION ALGORITHM

After refining the parameters the prime step is image segmentation, by allocating the pixels to the segments. This operation is performed by segmentation algorithm. The image segmentation algorithm consists of four steps ( )2 2 2 1 2 1 2 2 2 2 - - - ( ) 1 ( ) -( ) k k k k k k k k k k k F c µ µ µ ?? ? ? µ ? ? ? ? ? ? ? ? ? ? ? ? ? ? ? = ? . That is ( ) 2 2 1 1 2 2 2 1 1 2 2 2 1 2 0 0 1 exp 2 2(1) max 2 1 , , s k s k s k s k k k k k k k j j k k k k k x x y y L f x y dxdy µ µ µ µ ? ? ? ? ? ? ?? + ? VI.

5 EXPERIMENTAL RESULTS

To demonstrate the utility of the image segmentation algorithm developed in this paper, an experiment is conducted with six images taken from Berkeley images dataset (http://www.eecs. Step4) Assign each pixel into the corresponding j th region (segment) according to the maximum likelihood of the j th component L j . [1] [2] [3] [4]

Figure 1:

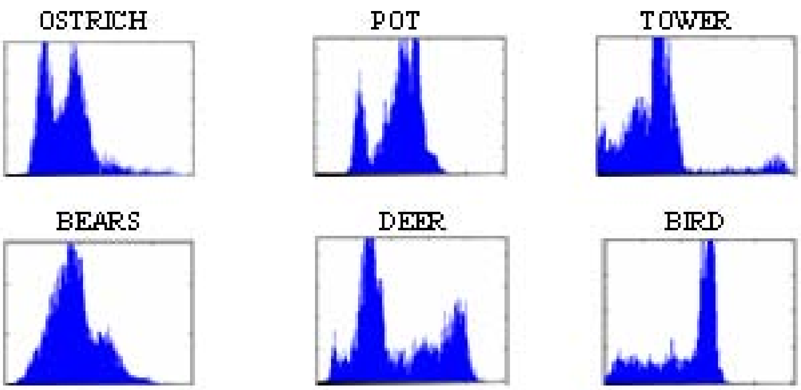


1

Figure 2: 1

IMAGE	OSTRICH	POT	TOWER	BEARS	DEER	BIRD
Estimate of K	2	3	4	2	4	3

Figure 3:



1k

Figure 4: 2k µ = 1k y

Table-2a Estimated Values of The Parameters For OSTRICH Image Number of image regions (K=2)				
Parameters	Estimation of Initial Parameters by K-means		Estimation of Final Parameters by EM-Algorithm	
	Regions(i)		Regions(i)	
	1	2	1	2
α_i	1/2	1/2	0.2627	0.7373
μ_{1i}	0.1781	0.1940	0.2054	0.2798
μ_{2i}	0.3321	0.7613	0.2505	0.7775
σ^2_{1i}	0.0016	0.0004	0.0287	0.0772
σ^2_{2i}	0.0126	0.0207	0.0747	0.0768
ρ_i	-0.4310	0.6996	-0.6163	0.2840

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Figure 5: Step 1) 2 1k ? , 2 2k ? , k ? and k ? for i= 1 , 2 ,

Table-2b Estimated Values of The Parameters For POT Image Number of image regions (K=3)						
Parameters	Estimation of Initial Parameters by K-means			Estimation of Final Parameters by EM-Algorithm		
	Regions(i)			Regions(i)		
	1	2	3	1	2	3
α_i	1/3	1/3	1/3	0.4888	0.2019	0.3093
μ_{1i}	0.5532	0.4946	0.1517	0.5505	0.5223	0.3089
μ_{2i}	0.2168	0.1125	0.1219	0.1958	0.0810	0.1106
σ^2_{1i}	0.0004	0.0027	0.0029	0.0248	0.0269	0.6202
σ^2_{2i}	0.0008	0.0018	0.0035	0.0358	0.0328	0.0469
ρ_i	0.1666	0.3570	-0.7230	-0.4604	0.9867	0.1373

Figure 6:

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Table-2c								
Estimated Values of The Parameters For TOWER Image Number of Image Regions (K =4)								
Parameters	Estimation of Initial Parameters by K-means				Estimation of Final Parameters by EM-Algorithm			
	Regions(i)				Regions(i)			
	1	2	3	4	1	2	3	4
α_i	1/4	1/4	1/4	1/4	0.1999	0.1523	0.1872	0.4606
μ_{1i}	0.1519	0.5699	0.1505	0.5738	0.4011	0.6276	0.1616	0.5743
μ_{2i}	0.1937	0.2789	0.6176	0.7724	0.2408	0.3519	0.5047	0.7721
σ^2_{1i}	0.0033	0.0073	0.0011	0.0006	0.1268	0.1045	0.0043	0.0213
σ^2_{2i}	0.0148	0.0148	0.0291	0.0059	0.1055	0.1696	0.6936	0.0539
ρ_i	0.1561	-0.0259	0.0386	-0.1086	0.9061	0.7744	-0.1902	0.1944

Figure 7: Figure 2 : 2 1i ? , 2 2i?

Table-2d				
Estimated Values of The Parameters For BEARS Image Number of Image Regions (K =2)				
Parameters	Estimation of Initial Parameters by K-means		Estimation of Final Parameters by EM-Algorithm	
	Regions(i)		Regions(i)	
	1	2	1	2
α_i	1/2	1/2	0.4531	0.5469
μ_{1i}	0.4787	0.2364	0.4867	0.4067
μ_{2i}	0.4532	0.2600	0.4171	0.3375
σ^2_{1i}	0.0027	0.0154	0.0560	0.0667
σ^2_{2i}	0.0129	0.0170	0.0786	0.1439
ρ_i	0.2044	-0.6378	0.1263	0.6274

Figure 8:

Figure 9:

and k ? .

? 1k µ , 2k µ , 2 1k ? , 2 ? 2k

by plotting the histogram of the pixel intensities of the whole image. The mixing parameter k ? and the region parameters 1k µ , 2k µ , 2 1k ? , 2 2k ? , k ? are unknown as prior. A commonly used method in initializing parameters is by drawing a random sample in the entire image data (Mclanchan G. and Peel D. (

Figure 10:

Substituting the final estimates of the model parameters, the probability density function of the feature vector of each image are estimated. Using the estimated probability density functions and the image segmentation algorithm given in section V, the image segmentation is done for each of the six images under consideration. The original and segmented images are shown in Figure **??**.

.1 PERFORMANCE EVALUATION

After conducting the experiment with the image segmentation algorithm developed in this paper, its performance is studied. The comparison is based on three performance measures namely, Probabilistic Rand Index (PRI) given by Unnikrishnan R. and et.al **??**2007), the Variation of Information (VOI) given by Meila M. (2005), and Global Consistency error (GCE) given by Martin D. and et al (2001). The objective of the segmentation methods are based on regional similarity measures in relations to their local neighborhood.

The performance of developed algorithm using finite left truncated bivariate Gaussian mixture model (FLTBGMM) is studied by computing the segmentation performance measures namely, PRI, GCE and VOI for the six images under study. The computed values of the performance measures for the developed algorithm and the earlier existing finite Gaussian mixture model (GMM) with K-means algorithm are presented in Table **??** for a comparative study. **??**, it is observed that all the image quality metrics for the images are meeting the standard criteria. This implies that using the proposed algorithm the images are retrieved accurately. A comparative study of proposed algorithm with that of algorithm based on finite Gaussian mixture model (GMM) and Finite left truncated bivariate Gaussian mixture model with K-means reveals that the mean square error of the proposed model is less than that of the finite GMM and FLTBGMM. Based on all other quality metrics also it is observed that the performance of the proposed model in retrieving the images is better than the finite Gaussian mixture model.

.2 VIII.

.3 CONCLUSION

In this paper we introduce a novel and new colour image segmentation method based on left truncated bivariate Gaussian mixture model. Here it is assumed that the colour image is characterized by HSI colour space, in which the Hue and Saturation values are non negative. they are characterized by left truncated Bivariate Gaussian mixture model. The left truncated bivariate Gaussian distribution includes the Bivariate Gaussian distribution is a limiting case when the truncation points tends to infinite. It also includes several platy, meso, lefty and skewed distributions as particular cases for different values of the parameters. The model parameters are estimated by using EMalgorithm. The initialization and the number of image segments are determined through K-means algorithm and moment method of estimation. The segmentation algorithm is developed with component maximum likelihood. The experimentation with six colour images reveals that this algorithm outperforms the existing algorithms in both image segmentation and image retrievals. The image quality metrics also supported the utility of the proposed algorithm. It is possible to develop image segmentation algorithm with finite mixture of doubly truncated multivariate Gaussian distribution with more image features which require further investigations.

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