Global Journal of Computer Science and Technology
Volume 11 Issue 17 Version 1.0 October 2011
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
Online ISSN: 0975-4172 & Print ISSN: 0975-4350

Studies on Image Segmentation Method Based On a New Symmetric Mixture Model with – K Means

By M.Seshashayee, K.Srinivasa Rao, Ch.Satyanarayana, P.Srinivasa Rao

GITAM University, Visakhapatnam

Abstract - In this paper we propose an image segmentation algorithm based on new-symmetric mixture model. Here the pixel intensities of the whole image are characterized through a new-symmetric mixture distribution, such that the statistical characteristics of the image coincide with that of the new symmetric distribution. Using the K-Means algorithm the number of image regions and initial estimates of the model parameters for the EM algorithm are obtained. The segmentation algorithm is proposed by component maximum likelihood under Bayesian frame work. The efficiency of the proposed method is studied with the five images taken from the Berkeley image dataset and computing the values image segmentation measures like global consistency error, probabilistic rand index and variation of information. A comparative study of the proposed model with Gaussian mixture model reveals that the proposed method performs better. The efficiency of the proposed method with respect to the image retrieval is also studied.

Keywords : Image Segmentation, New Symmetric Mix- ture Model, Image Quality Metrics, K-means algorithm, EM algorithm.

GJCST-H Classification : I.4.6, I.3.3

Studies on Image Segmentation Method Based On a New Symmetric Mixture Model with K – Means

M.Seshashayee[α], K.Srinivasa Rao[Ω], Ch.Satyanarayana[β], P.Srinivasa Rao[ψ]

Abstract - In this paper we propose an image segmentation algorithm based on new-symmetric mixture model. Here the pixel intensities of the whole image are characterized through a new-symmetric mixture distribution, such that the statistical characteristics of the image coincide with that of the new symmetric distribution. Using the K-Means algorithm the number of image regions and initial estimates of the model parameters for the EM algorithm are obtained. The segmentation algorithm is proposed by component maximum likelihood under Bayesian frame work. The efficiency of the proposed method is studied with the five images taken from the Berkeley image dataset and computing the values image segmentation measures like global consistency error, probabilistic rand index and variation of information. A comparative study of the proposed model with Gaussian mixture model reveals that the proposed method performs better. The efficiency of the proposed method with respect to the image retrieval is also studied.

Keywords : Image Segmentation, New Symmetric Mixture Model, Image Quality Metrics, K-means algorithm, EM algorithm.

I. Introduction

Image segmentation is a preprocessing step in image analysis and understanding. Much work has been reported in literature regarding image segmentation. Pal S.K. and Pal N.R (1993), Jahne (1995), Cheng et al (2001), Mantas Paulinas and Audrius Usinskas (2007) and Shital Raut et al (2009) have discussed various image segmentation methods.

The image segmentation methods are usually classified into three categories namely (i) segmentation methods based on histogram, threshold and edge based techniques, (ii) model based image segmentation methods and (iii) image segmentation based on other methods like graph, saddle point, neural networks, fuzzy logic etc., (Caillol H. et al (1993),Tolias Y.A. and Pamas S.M (1998), Brun L. (1998), Xu Y. et al (1998)). Among these methods model based image segmentation is more efficient since it preserves the neighborhood information and characterizes the features of the image region more accurately. Hence much emphasis is given for image segmentation based on finite Gaussian mixture model (Yamazaki et .al(1998) , Lie T. et al(1993), Zhang Z.H. et al (2003) and Nasios N. et al(2006)).

In Gaussian mixture model the whole image is characterized by the collection of several image regions, where each region is characterized by a Gaussian distribution. That is the pixel intensities in each image region follow a Gaussian distribution. This Gaussian assumption serves well only when the pixel intensities in each image region are meso-kurtic and symmetric. But in some images like natural scenes the pixel intensities of the image region may not be meso-kurtic even though they are symmetric. Hence to have an accurate analysis of the images, it is needed to develop image segmentation methods based on Non-Gaussian mixture models.

In Non-Gaussian symmetric mixture models the kurtosis plays a dominant role. Based on the kurtosis the Non-Gaussian models can be classified into two categories platy-kurtic and lepto-kurtic. In general many of the natural scenes will have image regions having platy-kurtic nature. That is the kurtosis of the pixel intensities in the image regions is less than three. One such model available in literature is new-symmetric distribution given by Srinivasa Rao K. et al (1997). The new-symmetric distribution is having kurtosis 2.52 and symmetric. So it is a platy-kurtic distribution. Hence to have an efficient image segmentation algorithm for images having platy-kurtic distributed pixel intensities in the image regions, we develop and analyze an image segmentation algorithm based on new-symmetric mixture model.

For developing the image segmentation algorithm we require the number of components in the image. This is obtained from K-means algorithm. The initial estimates of the model parameters are obtained from the moment estimates. The updated equations for estimating the model parameters through the EM algorithm are derived. The segmentation algorithm is also presented by taking component maximum likelihood. The efficiency of the proposed algorithm is studied through experimentation.

Author [α] : Department of CS, GITAM University, Visakhapatnam-45. E-mail : sesha_shayee@yahoo.co.in
Author [Ω] : Department of Statistics, Andhra University, Visakhapatnam-03. E-mail : ksraoau@yahoo.co.in
Author [β] : Department of CSE, JNTU-KAKINADA, KAKINADA E-mail : chsatyanarayana@yahoo.com
Author [ψ] : Department of CS&SE, Andhra University, Visakhapatnam-03. E-mail : peri.srinivasarao@yahoo.com

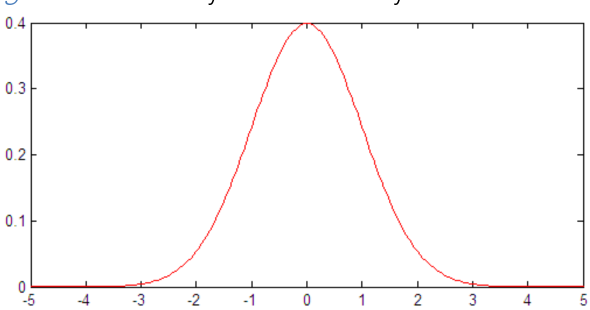
II. Finite Mixture of New Symmetric Distribution

In low level image analysis the entire image is considered as a union of several image regions. In each image region the image data is quantized by pixel intensities. For a given point (pixel) (x , y), the pixel intensity z = f(x , y) is a random variable, because of the fact that the brightness measured at a point in the image is influenced by various random factors like vision, lighting, moisture, environmental conditions etc,. To model the pixel intensities of the image region it is assumed that the pixel intensities of the region follow a new symmetric distribution given by Srinivasa Rao K. et al., (1997). The probability density function of the pixel intensity is

$$f(Z,\mu,\sigma^2)=\frac{\left(2+\left(\frac{z-\mu}{\sigma}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z-\mu}{\sigma}\right)^2}}{3\sigma\sqrt{2\pi}},-\infty<Z<\infty,-\infty<\mu<\infty,\sigma>0 \quad (1)$$

The probability curve of new symmetric distribution is shown in Figure 1.

Figure 1 : Probability curve of new symmetric distribution



Its central moments are

$$\mu_{2n}=\left[\frac{(n+\frac{3}{2})\Gamma(n+\frac{1}{2})}{(3/2)\sqrt{\pi}}\right]2^n\sigma^{2n} \quad \text{and} \quad \mu_{2n+1}=0 \quad (2)$$

The kurtosis of the distribution is $\beta_2=2.52$ (3)

The entire image is a collection of regions which are characterized by new symmetric distribution. Here, it is assumed that the pixel intensities of the whole image follow a K – component mixture of new symmetric distribution and its probability density function is of the form.

$$p(z)=\sum_{i=1}^{K}\alpha_i f_i(z/\mu_i,\sigma_i^2) \quad (4)$$

where, K is number of regions , $0\le \alpha_i \le 1$ are weights such that $\sum\alpha_i = 1$ and $f_i(z,\mu,\sigma^2)$ is as given in equation (1). α_i is the weight associated with ith region in the whole image.

In general the pixel intensities in the image regions are statistically correlated and these correlations can be reduced by spatial sampling (Lie.T and Sewehand. W(1992)) or spatial averaging (Kelly P.A. et al.(1998)) . After reduction of correlation the pixels are considered to be uncorrelated and independent. The mean pixel intensity of the whole image is

$$E(Z)=\sum_{i=1}^{K}\alpha_i\mu_i .$$

III. Estimation of The Model Parameters by EM Algorithm

In this section we derive the updated equations of the model parameters using Expectation Maximization (EM) algorithm. The likelihood function of the observations z1,z2,z3,…,zN drawn from an image is

$$L(\theta)=\prod_{S=1}^{N}p(z_s,\theta^{(l)}) .$$

That is $$L(\theta)=\prod_{S=1}^{N}\left(\sum_{i=1}^{K}\alpha_i f_i(z_s,\theta)\right)$$

$$\log L(\theta)=\sum_{s=1}^{N}\log\left(\sum_{i=1}^{K}\alpha_i f_i(z_s,\theta_i)\right),$$

Where $\theta=(\mu_i,\sigma_i^2,\alpha_i;i=1,2,...,K)$ is the set of parameters

$$\log L(\theta)=\sum_{s=1}^{N}\log\left[\sum_{i=1}^{K}\frac{\alpha_i\left(2+\left(\frac{z_s-\mu_i}{\sigma_i}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-\mu_i}{\sigma_i}\right)^2}}{3\sigma_i\sqrt{2\pi}}\right] \quad (5)$$

The first step of the EM algorithm requires the estimation of the likelihood function of the sample observations. The expectation of the log likelihood function of the sample is

$$Q\left(\theta;\theta^{(l)}\right)=E_{\theta^{(l)}}\left[\log L(\theta)/\bar{z}\right]$$

Following the heuristic arguments of Jeff A. Bilmes (1997) we have

$$Q\left(\theta;\theta^{(l)}\right)=\sum_{i=1}^{K}\sum_{s=1}^{N}\left(t_i(z_s,\theta^{(l)})\left(\log f_i(z_s,\theta)+\log\alpha_i\right)\right) \quad (6)$$

The updated equation of α for $(l+1)^{th}$ th estimate is

$$\alpha_i^{(l+1)}=\frac{1}{N}\sum_{s=1}^{N}t_i(z_s,\theta^{(l)})$$

$$= \frac{1}{N}\sum_{s=1}^{N}\left[\frac{\alpha_i^{(l)} f_i(z_s,\theta^{(l)})}{\sum_{i=1}^{K}\alpha_i^{(l)} f_i(z_s,\theta^{(l)})}\right] \qquad (7)$$

The updated equation of α at $(l+1)^{th}$ iteration is

$$\mu_i^{(l+1)} = \frac{\sum_{s=1}^{N} z_s t_i(z_s,\theta^{(l)}) - \sum_{s=1}^{N} t_i(z_s,\theta^{(l)})\left(\frac{2\sigma_i^{2(l)}\left(z_s-\mu_i^{(l)}\right)}{2\sigma_i^{2(l)}+\left(z_s-\mu_i^{(l)}\right)^2}\right)}{\sum_{s=1}^{N} t_i(z_s,\theta^{(l)})} \qquad (8)$$

where, $t_i(z_s,\theta^{(l)}) = \dfrac{\alpha_i^{(l+1)} f_i(z_s,\mu_i^{(l)},(\sigma_i^2)^{(l)})}{\sum_{i=1}^{K}\alpha_i^{(l+1)} f_i(z_s,\mu_i^{(l)}(\sigma_i^2)^{(l)})}$

The updated equation of σ_i^2 at $(l+1)^{th}$ iteration is

$$(\sigma_i^2)^{(l+1)} = \frac{2\sum_{s=1}^{N}(z_s-\mu_i^{(l+1)})^2\left(\frac{1}{2}-\frac{(\sigma_i^2)^{(l)}}{\left(2\sigma_i^{2(l)}+\left(z_s-\mu_i^{(l+1)}\right)^2\right)^2}\right)\left(t_i(z_s,\theta^{(l)})\right)}{\sum_{s=1}^{N} t_i(z_s,\theta^{(l)})} \qquad (9)$$

where $t_i(z_s,\theta^{(l)}) = \dfrac{\alpha_i^{(l+1)} f_i(z_s,\mu_i^{(l+1)},(\sigma_i^2)^{(l)})}{\sum_{i=1}^{K}\alpha_i^{(l+1)} f_i(z_s,\mu_i^{(l+1)},(\sigma_i^2)^{(l)})}$

IV. Initialization of The Parameters by K – Means

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 initially taken for K – Means algorithm is by plotting the histogram of the pixel intensities of the whole image. The number of peaks in the histogram can be taken as the initial value of the number of regions K.

The mixing parameters α_i and the model parameters μ_i, σ_i^2 are usually considered as known apriori. A commonly used method in initializing parameters is by drawing a random sample from the entire image Mclanchan G and Peel D (2000). This method performs well if the sample size is large and its computational time is heavily increased. When the sample size is small, some small regions may not be sampled. To overcome this problem we use the 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 the pixel joins a cluster.

After determining the final values of K (number of regions) , we obtain the initial estimates of μ_i, σ_i^2 and α_i for the i^{th} region using the segmented region pixel intensities with the method given by Srinivasa Rao et al.,(1997) for new symmetric distribution .The initial estimate α_i is taken as $\alpha_i = \frac{1}{K}$, where i = 1,2,...,K. The parameters μ_i and σ_i^2 are estimated by the method of moments as $\mu_i = \overline{z}$ and $\sigma_i^2 = \dfrac{4n}{3(n-1)}S^2$ where, S^2 is the sample variance.

V. Segmentation Algorithm

In this section, we present the image segmentation algorithm. After refining the parameters the prime step in image segmentation is allocating the pixels to the segments of the image. This operation is performed by Segmentation Algorithm. The image segmentation algorithm consists of four steps.

Step 1) Plot the histogram of the whole image.
Step 2) Obtain the initial estimates of the model parameters using K-Means algorithm and moment estimators as discussed in section 4
Step 3) Obtain the refined estimates of the model parameters μ_i, σ_i^2 and α_i for i=1,2,...,K by using the EM algorithm with the updated equations
Step 4) Assign each pixel into the corresponding j^{th} region (segment) according to the maximum likelihood of the j^{th} component L_j.
That is ,

$$L_j = \max_{j\in k}\left[(3\sigma_j\sqrt{2\pi})^{-1}\left(2+\left(\frac{z_s-\mu_j}{\sigma_j}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-\mu_j}{\sigma_j}\right)^2}\right],$$

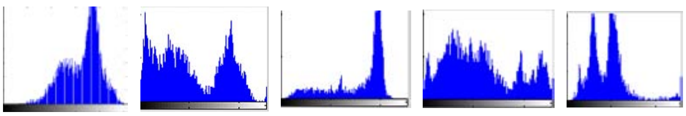
$$-\infty < z_s < \infty,\ -\infty < \mu_j < \infty, \sigma_j > 0$$

VI. Experimental Results

To demonstrate the utility of the image segmentation algorithm developed in this chapter, an experiment is conducted with five images taken from Berkeley images dataset (http://www.eecs.berkeley.edu/Research/Projects/CS/Vision/bsds/BSDS300/html),

The images HORSE, MAN, BIRD, BOAT and TOWER are considered for image segmentation. The pixel intensities of the whole image are taken as feature. The pixel intensities of the image are assumed to follow a mixture of new symmetric distribution. That is, the image contains K regions and pixel intensities in each image region follow a new symmetric distribution with different parameters. The number of segments in each of the five images considered for experimentation is determined by the histogram of pixel intensities. The histograms of the pixel intensities of the five images are shown in Figure 2.

Figure 2 : Histograms Of The Images



HORSE MAN BIRD BOAT TOWER

The initial estimates of the number of the regions K in each image are obtained and given in Table 1.

Table 1: Initial Estimates of K

IMAGE	HORSE	MAN	BIRD	BOAT	TOWER
Estimate of K	2	4	3	4	3

From Table 1, we observe that the image HORSE has two segments, images TOWER and BIRD have three segments each and images MAN and BOAT have four segments each. The initial values of the model parameters μ_i , σ_i^2 and α_i for i = 1, 2,...,K for each image region are computed by the method given in section 3.

Using these initial estimates and the updated equations of the EM Algorithm given in Section 3 the final estimates of the model parameters for each image are obtained and presented in tables 2.a, 2.b, 2.c, 2.c, 2.d ,and 2.e for different images.

Table : 2.a

Estimated Values of the Parameters for HORSE Image

Number of Image Regions (K =2)

Parameters	Estimation of Initial Parameters		Estimation of Final Parameters by EM Algorithm	
	Regions(i)		Regions(i)	
	1	2	1	2
α_i	1/2	1/2	0.39702	0.60298
μ_i	121.47	187.91	134.09	184.97
σ_i^2	609.82	426.21	1302.8	561.41

Table : 2.b

Estimated Values of the Parameters for MAN Image

Number of Image Regions (K =4)

Parameters	Estimation of Initial Parameters				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	0.24315	0.2306	0.34648	0.17977
μ_i	63.5	20.234	184.29	106.38	64.541	23.197	183.65	103.01
σ_i^2	190.98	165.05	547.54	361.45	497.03	214.15	509.25	1074.40

Table : 2.c

Estimated Values of the Parameters for BIRD Image

Number of Image Regions (K =3)

Parameters	Estimation of Initial Parameters			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	0.13161	0.66786	0.20053
μ_i	53.491	124.05	124.05	60.691	192.85	129.81
σ_i^2	535.4	513.93	513.93	857.07	86.799	1581.2

Table : 2.d

Estimated Values of the Parameters for BOAT Image
Number of Image Regions (K =4)

Parameters	Estimation of Initial Parameters				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	0.2570	0.24231	0.28458	0.22741
μ_i	34.98	216.5	81.146	131.13	41.008	212.7	81.062	128.11
σ_i^2	374.1	657.54	259.39	387.02	636.2	699.25	785.09	881.93

Table : 2.e

Estimated Values of The Parameters For TOWER Image
Number of Image Regions (K =3)

Parameters	Estimation of Initial Parameters			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	0.43267	0.051312	0.51602
μ_i	55.663	223.75	107.79	60.79	193.31	104.42
σ_i^2	276.53	1082.4	297.62	487.89	3140.4	404.79

Substituting the final estimates of the model parameters, the probability density function of pixel intensities of each image are estimated.

The estimated probability density function of the pixel intensities of the image HORSE is

$$f\left(z_s,\theta^{(l)}\right)=\frac{(0.39702)\left(2+\left(\frac{z_s-134.09}{36.0943}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-134.09}{36.0943}\right)^2}}{(36.0943)(3)\sqrt{2\pi}}$$
$$+\frac{(0.60298)\left(2+\left(\frac{z_s-184.97}{23.6941}\right)^2\right)^1 e^{\frac{-1}{2}\left(\frac{z_s-184.97}{23.6941}\right)^2}}{(23.6941)(3)\sqrt{2\pi}}$$

The estimated probability density function of the pixel intensities of the image MAN is

$$f\left(z_s,\theta^{(l)}\right)=\frac{(0.24315)\left(2+\left(\frac{z_s-64.541}{22.2942}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-64.541}{22.2942}\right)^2}}{(22.2942)(3)\ \ 2\pi}$$
$$+\frac{(0.2306)\left(2+\left(\frac{z_s-23.197}{14.6339}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-23.197}{14.6339}\right)^2}}{(14.6339)(3)\ \ 2\pi}$$
$$+\frac{(0.34648)\left(2+\left(\frac{z_s-183.65}{22.5666}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-183.65}{22.5666}\right)^2}}{(22.5666)(3)\ \ 2\pi}$$
$$+\frac{(0.17977)\left(2+\left(\frac{z_s-103.01}{32.7780}\right)^2\right)^2 e^{\frac{-1}{2}\left(\frac{z_s-103.01}{32.7780}\right)^2}}{(32.7780)(3)\ \ 2\pi}$$

The estimated probability density function of the pixel intensities of the image BIRD is

$$f\left(z_s,\theta^{(l)}\right)=\frac{(0.13161)\left(2+\left(\frac{z_s-60.691}{29.2758}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-60.691}{29.2758}\right)^2}}{(29.2758)(3)\sqrt{2\pi}}$$
$$+\frac{(0.66786)\left(2+\left(\frac{z_s-192.85}{9.3166}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-192.85}{9.3166}\right)^2}}{(9.3166)(3)\sqrt{2\pi}}$$
$$+\frac{(0.20053)\left(2+\left(\frac{z_s-129.81}{39.7643}\right)^2\right)^1 e^{\frac{-1}{2}\left(\frac{z_s-129.81}{39.7643}\right)^2}}{(39.7643)(3)\sqrt{2\pi}}$$

The estimated probability density function of the pixel intensities of the image BOAT is

$$f\left(z_s,\theta^{(l)}\right)=\frac{(0.2570)\left(2+\left(\frac{z_s-41.008}{25.1478}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-41.008}{25.1478}\right)^2}}{(25.14)(3)\sqrt{2\pi}}$$
$$+\frac{(0.24231)\left(2+\left(\frac{z_s-212.7}{26.4433}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-212.7}{26.4433}\right)^2}}{(26.4433)(3)\sqrt{2\pi}}$$
$$+\frac{(0.28458)\left(2+\left(\frac{z_s-81.062}{28.0195}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-81.062}{28.0195}\right)^2}}{(28.0195)(3)\sqrt{2\pi}}$$
$$+\frac{(0.22741)\left(2+\left(\frac{z_s-128.11}{29.6973}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-128.11}{29.6973}\right)^2}}{(29.6973)(3)\sqrt{2\pi}}$$

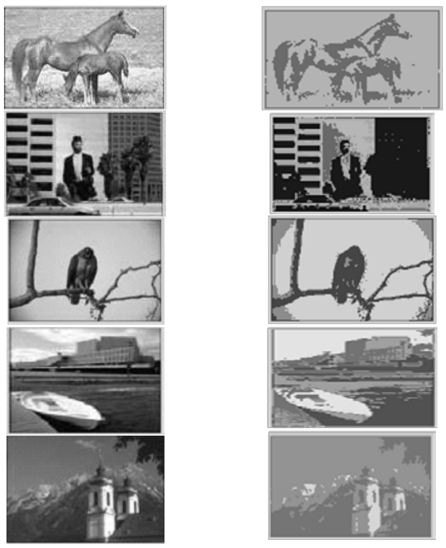
The estimated probability density function of the pixel intensities of the image TOWER is

$$f\left(z_s,\theta^{(l)}\right)=\frac{(0.43267)\left(2+\left(\frac{z_s-60.79}{22.0882}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-60.79}{22.0882}\right)^2}}{(22.0882)(3)\sqrt{2\pi}}$$
$$+\frac{(0.051312)\left(2+\left(\frac{z_s-193.31}{56.0393}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-193.31}{56.0393}\right)^2}}{(56.0393)(3)\sqrt{2\pi}}$$
$$+\frac{(0.51602)\left(2+\left(\frac{z_s-104.42}{20.1194}\right)^2\right)e^{\frac{-1}{2}\left(\frac{z_s-104.42}{20.1194}\right)^2}}{(20.1194)(3)\sqrt{2\pi}}$$

Using the estimated probability density function and image segmentation algorithm given in section 5, the image segmentation is done for the five images under consideration. The original and segmented images are shown in Figure 3.

Figure 3 : Original and Segmented Images

ORIGINAL IMAGES   SEGMENTED IMAGES



VII. Performance Evalution

After conducting the experiment with the image segmentation algorithm developed in this chapter, its performance is studied. The performance evaluation of the segmentation technique is carried by obtaining the three performance measures namely, (i) Probabilistic Rand Index (PRI), (ii) Variation Of Information (VOI) and (iii) Global Consistence Error (GCE). The performance of developed algorithm using finite new symmetric distribution mixture model (NSMM-K) is studied by computing the segmentation performance measures namely PRI, GCE, and VOI for the five 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 3 for a comparative study.

Table 3 : Segmentation Performace Measures

IMAGES	METHOD	PERFORMACE MEASURES		
		PRI	GCE	VOI
HORSE	GMM	0.9142	0.1737	1.8643
	NSMM-K	0.9283	0.1634	1.8403
MAN	GMM	0.9228	0.3107	1.8389
	NSMM-K	0.9342	0.1734	1.7875
BIRD	GMM	0.9106	0.1369	1.7479
	NSMM-K	0.9140	0.1352	1.7259
BOAT	GMM	0.9026	0.6485	1.7882
	NSMM-K	0.9174	0.6483	1.7542
TOWER	GMM	0.9102	0.1090	1.8643
	NSMM-K	0.9246	0.0981	1.7988

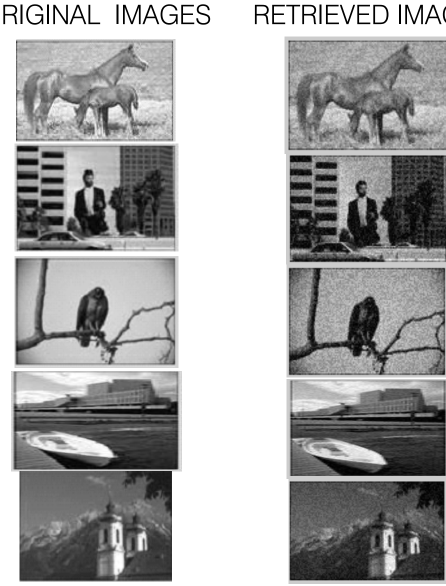
From table 3 it is observed that the PRI values of the proposed algorithm for the five images considered for experimentation are less than that of the values from the segmentation algorithm based on finite Gaussian mixture model with K-means. Similarly GCE and VOI values of the proposed algorithm are less than that of Finite Gaussian Mixture Model. This reveals that the proposed algorithm outperforms the existing algorithm based on the finite Gaussian mixture model. When the kurtosis parameter of each component of the model is zero, the model reduces to finite Gaussian mixture model and even in this case the algorithm performs well.

After developing the image segmentation method it is needed to verify the utility of segmentation in model building of the image for image retrieval.The performance evaluation of the retrieved image can be done by subjective image quality testing or by objective image quality testing. The objective image quality testing methods are often used since the numerical results of an objective measure allows a consistent comparison of different algorithms. There are several image quality measures available for performance evaluation of the image segmentation method. An extensive survey of quality measures is given by Eskicioglu A.M. and Fisher P.S. (1995). For the performance evaluation of the developed segmentation algorithm, we consider the image quality measures like average difference, maximum distance, image fidelity, mean square error, signal to noise ratio and image quality index.

Using the estimated probability density functions of the images under consideration the retrieved images are obtained and are shown in Figure 4.

Figure 4 : The Original and Retrieved Images

ORIGINAL IMAGES   RETRIEVED IMAGES



The image quality measures are computed for the five retrieved images HORSE, MAN, BIRD, BOAT AND TOWER using the proposed model and FGMM with K-means and their values are given in the Table 4.

Table 4 : Comparative Study of Image Quality Metrics

IMAGE	Quality Metrics	FGMM	FNSDMM with K-Means	Standard Limits
HORSE	Average Difference	0.5011	0.44135	Close to 1
	Maximum Distance	1.0000	1.0000	Close to 1
	Image Fidelity	1.0000	1.0000	Close to 1
	Mean Square Error	0.5011	0.4414	Close to 0
	Signal to Noise Ratio	5.6542	5.9301	As big as possible
	Image Quality Index	1.0000	1.0000	Close to 1
MAN	Average Difference	0.4858	0.50021	Close to 1
	Maximum Distance	1.0000	1.0000	Close to 1
	Image Fidelity	1.0000	1.0000	Close to 1
	Mean Square Error	0.4995	0.5079	Close to 0
	Signal to Noise Ratio	5.6828	5.6251	As big as possible
	Image Quality Index	1.0000	1.0000	Close to 1
BIRD	Average Difference	0.4939	0.6573	Close to 1
	Maximum Distance	1.0000	1.0000	Close to 1
	Image Fidelity	1.0000	1.0000	Close to 1
	Mean Square Error	0.8590	0.5050	Close to 0
	Signal to Noise Ratio	5.6861	4.4842	As big as possible
	Image Quality Index	1.000	1.0000	Close to 1
BOAT	Average Difference	0.5039	0.6217	Close to 1
	Maximum Distance	1.0000	1.0000	Close to 1
	Image Fidelity	1.0000	1.0000	Close to 1
	Mean Square Error	0.7931	0.5070	Close to 0
	Signal to Noise Ratio	5.6318	4.6573	As big as possible
	Image Quality Index	1	1.0000	Close to 1
	Average Difference	0.4936	0.6640	Close to 1
	Maximum Distance	1.0000	1.0000	Close to 1
TOWER	Image Fidelity	0.9999	0.9999	Close to 1
	Mean Square Error	0.8788	0.5076	Close to 0
	Signal to Noise Ratio	5.6870	4.4347	As big as possible
	Image Quality Index	1.0000	1.0000	Close to 1

From the Table 4, it is observed that all the image quality measures for the five 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 reveals that the MSE of the proposed model is less than that of the finite Gaussian mixture model. 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.

VIII. Conclusion

An image segmentation algorithm based on new symmetric mixture model with K-means is developed and evaluated. This algorithm is more suitable for the images having platy-kurtic image regions. The new symmetric mixture model is capable of characterizing several natural images with kurtosis close to 2.52. The updated equations of the model parameters are derived through EM algorithm under Bayesian framework. The estimated probability density function of the pixel intensities in the whole image is useful for the image retrieval. The experimental results revealed that the proposed method out performs the existing Gaussian mixture model in both image segmentation and image retrieval.

References Références Referencias

1. Caillol H. et al (1993), "Fuzzy Random Fields and Unsupervised Image Segmentation", IEEE Transactions on Geo-Science and Remote Sensing, Vol.31, No.4, pp.801-810.
2. Cheng et al (2001) "Color Image Segmentation: Advances and Prospects" Pattern Recognition, Vo1.34, pp 2259-2281.
3. D . Martin, C. Fowlkes,D. Tal, and J.Malik, (2001) " A database of human Segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics," in proceedings of 8th International Conference on Computer vision, Vol.2, pp.416-423.
4. Eskicioglu M.A and Fisher P.S (1995) "Image Quality Measures and their Performance", IEEE Transactions On Communications, Vol.43, No.12.
5. Fang Qian et al (2002), "Gaussian Mixture Model For Relevance Feedback In Image Retrieval", IEEE

Transactions on Image Processing, Vol.1 , pp. 229-232.
6. Jahne (1995), " A Practical Hand Book on Image segmentation for Scientific Applications, CRC Press.
7. Jeff A. Bilmes (1997), " A Gentle Tutorial of the EM Algorithm and its application to Parameter Estimation for Gaussian Mixture and Hidden Markov Models", Technical Report, University of Berkeley, ICSI-TR-97-021.
8. Kelly P.A. et al (1988), "Adaptive segmentation of speckled images using a hierarchical random field model". IEEE Transactions Acoust. Speech. Signal Processing, Vol.36, No.10, Pg.1628-1641.
9. Lie. T and Sewehand.W(1992), " Statistical approach to X-ray CT imaging and its Applications in image analysis", IEEE Trans. Med. Imag. Vol.11, No.1, Pg 53-61.
10. Lie T. et al.(1993), " Performance evaluation of Finite normal mixture model based image segmentation, IEEE Transactions on Image processing, Vol .12(10), pp 1153-1169.
11. Mantas Paulinas and Andrius Usinskas (2007), "A survey of genentic algorithms applications for image enhancement and segmentation", Information Technology and control, Vol.36, No.3, pp. 278-284.
12. Mclanchlan G. And Krishnan T(1997)., " The EM Algorithm and Extensions", John Wiley and Sons, New York -1997.
13. Mclanchlan G. and Peel.D(2000), " The EM Algorithm For Parameter Estimations", John Wiley and Sons, New York -2000.
14. Meila M. (2005)"Comparing Clustering – An axiomatic view," in proceedings of the 22nd International Conference on Machine Learning, pp. 577-584.
15. Nasios N., A.G.Bors,(2006) " Variational learning for Gaussian Mixtures", IEEE Transactions on Systems, Man , and Cybernatics - Part B : Cybernatics, Vol36(4), pp. 849-862.
16. Pal S.K. and Pal N.R(1993), " A Review On Image Segmentation Techniques",Pattern Recognition, Vol.26, N0.9, pp. 1277-1294.
17. Rose H. Turi (2001)," Cluster Based Image Segmentation", phd Thesis, Monash University, Australia.
18. Shital Raut et al (2009), "Image segmentation- A State-Of-Art survey for Prediction", International conference on Adv. Computer control, pp.420-424.
19. Srinivas Rao K. ,C.V.S.R.Vijay Kumar, J.Lakshmi Narayana,(1997)"On a New Symmetrical Distribution ", Journal of Indian Society for Agricultural Statistics, Vol.50(1), pp. 95-102.
20. Srinivas Y. and Srinivas Rao K. (2007), "Unsupervised image segmentat using finite doubly truncated Gaussian mixture model and Hierarchial clustering ", Journal of Current Science,Vol.93,No.4, pp. 507-514.
21. "The Berkeley segmentation dataset" http://www.eecs. berkeley.edu /Research/ Projects /CS/vision/bsds/BSDS300/html/dataset/images.html.
22. Tolias Y.A. and Pamas S.M. (1998), " Image Segmentation by a Fuzzy clustering algorithm using adaptive spatially constrained membership functions", IEEE Transactions on Image Processing, pp. 359-369.
23. Unnikrishnan R. et al (2007), " Toward objective evaluation of image segmentation algorithms," IEEE Trans.Pattern Analysis and Machine Intelligence . Vol.29, No.6, pp. 929-944.
24. Xu Y. et al (1998), "A segmentation algorithm for noisy images, design and evaluation", Pattern Recognition letters, Vol. 19, pp. 1213-1224.
25. Yamazaki T. (1998), "Introduction of EM algorithm into color image segmentation," in Proceedings of ICIRS'98, pp. 368–371.
26. Yiming WU et al (2003), "Unsupervised Color Image Segmentation Based On Gaussian Mixture Models" Proceedings Of 2003 Joint Conference At The 4th International Conference On Information, Communication and Signal Processing, Vol.1, pp. 541-544.
27. Zhang Z.H. et al(2003)., " EM Algorithms for Gaussian Mixtures with Split-and- merge Operation", Pattern Recognition, Vol. 36(9),pp. 1973-1983.