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Image Segmentation for Animal Images using Finite Mixture of Pearson type VI Distribution

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K. Srinivasa Rao [α], P. Chandra Sekhar [σ] & P. Srinivasa Rao [ρ]

Abstract- Image Segmentation is one of the significant tool for analyzing images, the feature vector of the images are different for different types of images. In remote sensing, Environmental ecological systems, forest studies, conservation of rare animals, the animal images are more important. In this paper we developed and analyze an image segmentation algorithm using mixture of Pearson Type VI Distribution. The Pearsonian Type VI Distribution will characterize the image regions of animal images. The appropriateness Pearsonian Type VI distribution for the pixel intensities of image region in animal images is carried by fitting Pearsonian Type VI Distribution to set of animal images taken from Berkeley image data set. The image segmentation algorithm is developed using EM algorithm for estimating the parameters of the model and maximum likelihood for image component under Bayesian framework. For fast convergence of EM algorithm the initial estimates of the model parameters are obtained by dividing the whole image into K image regions using K-means and Hierarchical clustering algorithm and utilizing the moment method of estimates. The performance of proposed algorithm is studied by conducting an experiment with set of animal images and computing image quality metrics such as PRI, GCE and VOI. A comparative study of developed image segmentation by Gaussian Mixture model and found the proposed algorithm performed better for animal images due to asymmetrically distributed nature of pixel intensities in the image regions.

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I. Introduction

In image processing and retrievals image analysis plays a dominant role. The major task in image analysis is extracting useful information using features of the image. Generally image analysis techniques broadly grouping into groups namely (1) Structural methods (2) Statistical methods Raj Kumar et al (2011), among these two groups statistical methods are much popular. In Statistical methods one of the prime considerations is dividing whole image into different image regions using probability distributions. This type of method is usually referred as image Segmentation.

Much work has been reported in literature regarding image segmentation methods. Pal S.K and Pal N. R. (1993), Cheng et al (2001), Srinivasa et al (2007), Srinivas Y et al (2010), Prasad Reddy et al (2007) have reviewed the image segmentation methods. There is no unique image segmentation method available for analyzing all images. The image segmentation is basically dependent on type of images. The image broadly categorized into four types of categories . They are (1) Images on Earth (2) images of Humans and animals (3) images on sky (4) images on Water and (5) images of Nature. Among these categories the images of Human beings and Animals are in different in nature and features are associated with these images are different from others in some statistical sense. These images are Skewed in nature. Hence the image segmentation methods based on Gaussian mixture model given by Cheng et al (2001), Yamazaki T. et al (1998), Zhang Z.H et al (2003), Lie T. et al (1993) may not suit well. Even the methods given by Sesha sayee et al (2011), Srinivasa et al (2011) are also may not suit since these methods also focus on symmetry of the pixel intensities in the image region. Hence to have suitable and more appropriate image segmentation methods for animals, an image segmentation method using a mixture of Pearsonian Type VI Distribution is developed and analyzed. Here it is assumed that whole image is characterized by a mixture of Pearsonian Type VI probability model. The Pearsonian Type VI Distribution is skewed in nature having long upper tails. This distribution also includes several distributions as particular case. From the Berkeley image data set collected over animal images. It is evident that the pixel intensities of these images are well categorized by mixture of Pearsonian Type VI Distribution. The model parameters are estimated by updated equations of EM algorithm. The initial values of the model parameters of EM Algorithm are carried using Histograms of the whole image and K-means and Hierarchical clustering Algorithm and moment method of estimates. The image segmentation algorithm is developed through Maximum Likelihood component under Bayesian frame. The performance of image segmentation algorithm is skewed using image quality metrics and ground truth values. The comparative study of proposed algorithm with that of Gaussian Mixture Model is also carried.

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II. Mixture of Pearson Type VI Distribution

Usually the entire image is considered as a union of several image regions in low level image analysis and the image data is quantified by pixel intensities in each image region. Because of the fact that the brightness measured at a point in the image is influenced by various random factors like environmental conditions, vision, moisture, lighting etc, the pixel intensity $z = f(x, y)$ for a given point (pixel) (x, y) is a random variable. It is generally assumed that the pixel intensities of the region follow a Pearson Type VI distribution in order to model the pixel intensities of the animal and human image regions. The probability density function of the pixel intensity is

$$f_i(z / a_{i1}, q_{i1}, q_{i2}) = \frac{(z_s - a_i)^{q_{i2}} (z_s)^{-q_{i1}}}{(a_i)^{(q_{i2}-q_{i1}+1)} B(q_{i1} - q_{i2} - 1, q_{i2} + 1)} \quad ,(1)$$

$$a_i \le z_i < \alpha$$

The entire animal and human image is a collection of regions which are characterized by Pearson Type VI distribution. Here, it is assumed that the pixel intensities of the whole image follows a K – component mixture of Pearson Type VI distribution and its probability density function is of the form

$$p(z) = \sum_{i=1}^{K} \alpha_i \, f_i(z / a_{i1}, q_{i1}, q_{i2}) \quad (2)$$

where, K is number of regions , $0 \le \alpha_i \le 1$ are weights such that $\sum \alpha_i = 1$ and $f_i(z / a_{i1}, q_{i1}, q_{i2})$ is as given in equation (1). In the whole image α_i is the weight associated with i[th] region. Usually the intensities of the pixel in the image regions are statistically correlated and can be reduced by spatial averaging (Kelly P.A. et al (1998)) or spatial sampling (Lei T. and Sewehand W. (1992)) .The pixels are considered to be uncorrelated and independent after reduction of correlation. 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 $z_1, z_2, \ldots, z_N$ drawn from an image is

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

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

Where $\theta = (a_{i1}, q_{i1}, q_{i2}, \alpha_i; i = 1, 2, \ldots, K)$ is the set of parameters.

$$\log L(\theta) = \sum_{s=1}^{N} \log \left[\sum_{i=1}^{K} \frac{\alpha_i (z_s - a_i)^{q_{i2}} (z_s)^{-q_{i1}}}{(a_i)^{(q_{i2}-q_{i1}+1)} B(q_{i1} - q_{i2} - 1, q_{i2} + 1)} \right] \quad , (3)$$

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

a) E-Step

In the expectation (E) step, the expectation value of log $L(\theta)$ with respect to the initial parameter vector $\theta^{(0)}$ is

$$Q\left(\theta; \theta^{(0)}\right) = E_{\theta^{(0)}} \left[\log L(\theta) / \bar{z}\right]$$

Given the initial parameters $\theta^{(0)}$, one can compute the density of pixel intensity z_s as

$$p(z_s, \theta^{(l)}) = \sum_{i=1}^{K} \alpha_i^{(l)} f_i(z_s, \theta^{(l)})$$

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

$$\text{This implies } \log L(\theta) = \sum_{s=1}^{N} \log \left(\sum_{i=1}^{K} \alpha_i f_i(z_s, \theta^{(l)}) \right) \quad (4)$$

The conditional probability of any observation z_s, belongs to any region K is

$$t_k(z_s, \theta^{(l)}) = \left[\frac{\alpha_k^{(l)} f_k(z_s, \theta^{(l)})}{p(z_s, \theta^{(l)})} \right] = \left[\frac{\alpha_k^{(l)} f_k(z_s, \theta^{(l)})}{\sum_{i=1}^{K} \alpha_i^{(l)} f_i(z_s, \theta^{(l)})} \right]$$

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

$$Q\left(\theta; \theta^{(l)}\right) = \sum_{i=1}^{K} \sum_{s=1}^{N} \left(t_i(z_s, \theta^{(l)}) \left(\log f_i(z_s, \theta^{(l)}) + \log \alpha_i^{(l)} \right) \right) \quad (5)$$

But we have

$$f_i(z / a_{i1}, q_{i1}, q_{i2}) = \frac{(z_s - a_i)^{q_{i2}} (z_s)^{-q_{i1}}}{(a_i)^{(q_{i2}-q_{i1}+1)} B(q_{i1} - q_{i2} - 1, q_{i2} + 1)}$$

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

b) M-Step

For obtaining the estimation of the model parameters one has to maximize $Q\left(\theta;\theta^{(l)}\right)$ such that $\sum\alpha_i = 1$. This can be solved by applying the standard solution method for constrained maximum by constructing the first order Lagrange type function,

$$S=\left[E(\log L(\theta^{(l)}))+\lambda\left(1-\sum_{i=1}^{K}\alpha_i^{(l)}\right)\right] \tag{6}$$

where, λ is Lagrangian multiplier combining the constraint with the log likelihood function to be maximized.

Hence, $\frac{\partial S}{\partial\alpha_i}=0$. This implies

$$\frac{\partial}{\partial\alpha_i}\left[\sum_{i=1}^{K}\sum_{s=1}^{N}t_i(z_s,\theta^{(l)})\left[\log\left[\frac{(z_s-a_i)^{q_{i2}}(z_s)^{-q_{i1}}}{(a_i)^{(q_{i2}-q_{i1}+1)}B(q_{i1}-q_{i2}-1,q_{i2}+1)}\right]+\log\alpha_i\right]\right]$$
$$+\lambda\left(1-\sum_{i=1}^{K}\alpha_i\right)=0$$

This implies $\sum_{i=1}^{N}\frac{1}{\alpha_i}t_i(z_s,\theta^{(l)})+\lambda=0$

Summing both sides over all observations, we get λ = -N Therefore $\hat{\alpha}_i=\frac{1}{N}\sum_{s=1}^{N}t_i(z_s,\theta^{(l)})$ The updated equation of α_i for $(l+1)^{\text{th}}$ iteration is

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

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

Therefore $\frac{\partial}{\partial a_i}Q\left(\theta;\theta^{(l)}\right)=0$ implies $E\left[\frac{\partial\log L(\theta;\theta^{(l)})}{\partial a_{i1}}\right]=0$

$$\frac{\partial}{\partial a_i}\left[\sum_{i=1}^{K}\sum_{s=1}^{N}\left(t_i(z_s,\theta^{(l)})\left(\log f_i(z_s,\theta^{(l)})+\log\alpha_i^{(l)}\right)\right)\right]=0$$

The updated equation of a_i at $(l+1)$th iteration is

$$a_i^{(l+1)}=\sum_{s=1}^{N}\left[\frac{-(q_{i2}^{(l)}-q_{i1}^{(l)}+1)\left(z_s-a_i^{(l)}\right)t_i(z_s,\theta^{(l)})}{t_i(z_s,\theta^{(l)})q_{i2}^{(l)}}\right]$$

For updating the parameter q_{i1} , i = 1, 2, …, K we consider the derivative of $Q\left(\theta;\theta^{(l)}\right)$ with respect to q_{i1} and equate it to zero. We have

$$Q\left(\theta;\theta^{(l)}\right)=E\left[\log L(\theta;\theta^{(l)})\right]$$

Therefore $\frac{\partial}{\partial q_{i1}}Q\left(\theta;\theta^{(l)}\right)=0$ implies $E\left[\frac{\partial\log L(\theta;\theta^{(l)})}{\partial q_{i1}}\right]=0$

$$\frac{\partial}{\partial q_{i1}}\left[\sum_{i=1}^{K}\sum_{s=1}^{N}\left(t_i(z_s,\theta^{(l)})\left(\log f_i(z_s,\theta^{(l)})+\log\alpha_i^{(l)}\right)\right)\right]=0$$

$$q_{i1}=1-\sum_{s=1}^{N}\left[\frac{t_i(z_s,\theta^{(l)})}{\left[\left[\log\frac{a_i}{z_s}-\psi_0(q_{i1}-q_{i2}-2+1)+\psi_0(q_{i1}-1)\right]t_i(z_s,\theta^{(l)})\right]}\right] \tag{8}$$

The updated equation of q_{i1} at $(l+1)$th iteration is

$$q_{i1}^{(l+1)}=1-\sum_{s=1}^{N}\left[\frac{t_i(z_s,\theta^{(l)})}{\left[\left[\log\frac{a_i}{z_s}-\psi_0(q_{i1}^{(l)}-q_{i2}^{(l)}-2+1)+\psi_0(q_{i1}^{(l)}-1)\right]t_i(z_s,\theta^{(l)})\right]}\right] \tag{9}$$

For updating the parameter q_{i2} , i = 1, 2, …, K we consider the derivative of $Q\left(\theta;\theta^{(l)}\right)$ with respect to q_{i2} and equate it to zero. We have

$$Q\left(\theta;\theta^{(l)}\right)=E\left[\log L(\theta;\theta^{(l)})\right]$$

Therefore $\frac{\partial}{\partial q_{i2}}Q\left(\theta;\theta^{(l)}\right)=0$ implies $E\left[\frac{\partial\log L(\theta;\theta^{(l)})}{\partial q_{i2}}\right]=0$

$$\frac{\partial}{\partial q_{i2}}\left[\sum_{i=1}^{K}\sum_{s=1}^{N}\left(t_i(z_s,\theta^{(l)})\left(\log f_i(z_s,\theta^{(l)})+\log\alpha_i^{(l)}\right)\right)\right]=0$$

$$q_{i2}=\frac{\sum_{s=1}^{N}t_i(z_s,\theta^{(l)})}{\sum_{s=1}^{N}\left[\log\frac{(z_s-a_i)}{a_i}+\psi_0(q_{i1}-q_{i2}-2+1)-\psi_0(q_{i2})\right]t_i(z_s,\theta^{(l)})} \tag{10}$$

The updated equation of q_{i2} at $(l+1)$th iteration is

$$q_{i2}^{(l+1)}=\frac{\sum_{s=1}^{N}t_i(z_s,\theta^{(l)})}{\sum_{s=1}^{N}\left[\log\frac{(z_s-a_i)}{a_i}+\psi_0(q_{i1}^{(l)}-q_{i2}^{(l)}-2+1)-\psi_0(q_{i2}^{(l)})\right]t_i(z_s,\theta^{(l)})} \tag{11}$$

Where $t_i(z_s,\theta^{(l)})=\frac{\alpha_i^{(l)}f_i(z_s,\theta^{(l)})}{\sum_{i=1}^{K}\alpha_i^{(l)}f_i(z_s,\theta^{(l)})}$

IV. Initialization of the Parameters by K – Means and Hierarchical Algorithm

Generally the efficiency of the EM algorithm depends upon the count of the regions in the image, during the estimation of the parameters. The number of mixture components 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 q_{i1}, q_{i2} are usually considered as known apriori. Drawing a random sample from the entire image (Mclanchan G. and Peel D. (2000)) is the most commonly used method for initializing parameters. This method shows better performance, if the sample size is large and its computational time is heavily increased. When the sample size is small, there are some small regions which may not be sampled. To divide the whole image into various homogeneous regions we use the K – Means algorithm. In this algorithm the centroids of the clusters are recomputed as soon as the pixel joins a cluster.

a) K-Means Clustering Algorithm

It is one of the simplest clustering technique with a primary goal to find the partition of the data which minimizes the squared error or the sum of squared distances between all the points and their respective cluster centers (Rose H. Turi, (2001)). This K-means algorithm uses an iterative procedure and this procedure 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.

In the above algorithm, once only if all points have been allocated to their closed cluster centre then the cluster centers are updated. The advantage of this algorithm is that it is a very simple method, and 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 the K-Means algorithm 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 (Rose H. Turi, (2001)). Success of K-means algorithm depends on the parameter K, number of clusters in image.

After determining the final values of K (number of regions) , we obtain the initial estimates of a_i, q_{i1}, q_{i2} and α_i for the i^{th} region using the segmented region pixel intensities with Pearson Type VI distribution .The initial estimate α_i is taken as $\alpha_i=1/K$, where i = 1,2,...,K. The parameters q_{i1} and q_{i2} are estimated by the method of moments as first moment μ_1 and its three central moments (μ_2, μ_3 and μ_4).

b) Hierarchical Clustering Algorithm

In order to utilize the EM algorithm we have to initialize the parameter α_i and the model parameters q_{i1}, q_{i2} which are generally considered as known apriori. The initial values of α_i can be taken as $\alpha_i=1/K$ where, K is the number of image regions obtained from the Hierarchical clustering algorithm (Marr D. et al (1980)). The steps involved in hierarchical clustering algorithm are as follows.

Step 1: Start by assigning each item to a segment. Each of the N items, are associated with N segments, each containing just one item. Let the distances (similarities) between the segments be the same as the distances (similarities) between the items they contain.

Step 2: Find the closest (most similar) pair of segments and merge them into a single segment. The number of segments is now reduced by one. Compute distances (similarities) between the new segments and each of the old segments.

Step 3: Repeat steps 2 and 3 until all items are segmented.

Step 3 can be done in different ways, namely i) Single-Linkage ii) Complete-Linkage and iii) Average-Linkage segmenting. We consider the Average - Linkage methodology. Average-Linkage segmenting (also called the unweighted pair-group method using arithmetic averages), is one of the most widely used hierarchical clustering algorithms. The average linkage algorithm is obtained by defining the distance between two segments to be the average distance between a point in one segment and a point in the other segment. The algorithm is an agglomerative scheme that erases rows and columns in the proximity matrix as old segments are merged into new ones.

The proximity matrix is $D = [d(i,j)]$. The segments are assigned sequence numbers *0,1.., (n-1)* and $L(k)$ is the level of the K^{th} segment. A segment with a sequence number m is denoted by *(m)* and the proximity between segments *(r)* and *(s)* is denoted *d [(r), (s)]*. The algorithm is composed of the following steps: Begin with the disjoint segment having level $L(0) = 0$ and sequence number m = 0.

Find the average dissimilar pair of segments in the current segment, say pair *[(r), (s)]*,for all pairs of segments in the current segment.

1. Increment the sequence number: $m = m + 1$. Merge segments (r) and (s) into a single segment to form the next segmenting m. Set the level of this segmenting to $L(m) = d[\,(r), (s)\,]$.
2. Update the proximity matrix, D, by deleting the rows and columns corresponding to segments (r)

and (s) and adding a row and column corresponding to the newly formed segment. The proximity between the new segment, denoted (r, s) and old segment(K)is defined in this way.

$$d_{(r,s)\,K} = \frac{\sum_i \sum_j d(i,j)}{N_{(r,s)}\, N_K}$$

where *d(i, j)* is the distance between object i in the cluster *(r, s)* and object j in the cluster K, and $N_{(r,s)}$ and $N_{(k)}$ are the number of items in the clusters *(r, s)* and K respectively. The above procedure is repeated till the distance between two clusters is less than the specified threshold value.

We obtain the initial estimates of q_{i1}, q_{i2} and α_i for the i[th] region using the segmented region pixel intensities with the moment method given by Pearsonian Type VI distribution, only after determining the final values of K (number of regions). After getting these initial estimates, the final refined estimates of the parameters through EM algorithm given in section (III) is obtained.

V. Segmentation Algorithm

In this section, the characteristics of the image segmentation algorithm are projected. After refining the parameters, the first step in image segmentation is allocating the pixels to the segments of the image. This operation is performed by Segmentation Algorithm which 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 estimates for each image region as discussed in section IV.

Step 3: Obtain the refined estimates of the model parameters q_{i1},q_{i2} and α_i for i=1, 2, ..., K using the EM algorithm with the updated equations given by (7), (9) and (11) respectively in section III.

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

$$L_j = \max_{j \in k} \left[\frac{(z_s - a_i)^{q_{j2}} (z_s)^{-q_{j1}}}{(a_j)^{(q_{j2}-q_{j1}+1)} \beta(q_{j1} - q_{j2} - 1, q_{j2} + 1)} \right],$$

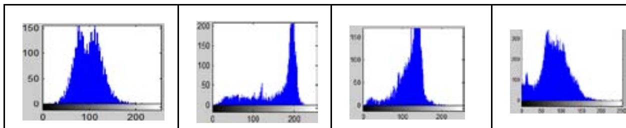
$$a_i \le z_i < \alpha \quad -\infty < q_{j1}, q_{j2} < \infty.$$

VI. Experimental Results

The performance of the developed a segmentation method for the natural images, which are considered on the earth. For implementing this algorithm, we need to initialize the model parameters, which are usually done by using moment method of estimations. Initially the feature vector is divided into different segmented regions by making use of non-parametric methods of segmentation namely K-means algorithm and Hierarchical clustering algorithms.

An experiment is conducted with four images taken from Berkeley images dataset (http:// www. eecs. berkeley.edu/Research/Projects/CS/Vision/bsds/BSDS300/html). The images FACE, EAGLE, NEST BIRD and TIGER, are considered for image segmentation in order to demonstrate the utility of the image segmentation algorithm. The pixel intensities of the whole image are taken as feature. The pixel intensities of the image are always assumed to follow a mixture of Pearson Type VI distribution.

That is, the image contains K regions and pixel intensities in each image region follow a Pearson Type VI distribution with different parameters. The number of segments in each of the four images considered for experimentation are determined by the histogram of pixel intensities. The histograms of the pixel intensities of the four images are shown in Figure 1.



TIGER	EAGLE	NEST BIRD	FACE

Figure 1 : Histograms Of The Images

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	TIGER	EAGLE	NEST BIRD	FACE
Estimate of K	2	3	4	4

From Table 1, we observe that the image TIGER has two segments, images EAGLE has three segments and images NEST BIRD AND FACE have four segments each. The initial values of the model parameters mi1,mi2, qi1,qi2 and αi for i = 1, 2, …, K , for each image region are computed by the method given in section III.

By making use of these initial estimates and the updated equations of the EM Algorithm given in Section III, the final estimates of the model parameters for each image are obtained and presented in Tables 2.a,2.b, 2.c, and 2.d for different images.

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Table-2.a

Estimated Values Of The Parameters For TIGER Image Number of Image Regions (K =2)				
Parameters	Estimation of Initial Parameters		Estimation of Final Parameters by EM Algorithm	
	Image Region		Image Region	
	1-TYPEI	2-TYPEVI	1-TYPEI	2-TYPEVI
α_i	0.500	0.500	0.988622	0.011378
a_{i1}	-97.4751	a_i =453.1814	-0.00316	a_i =1
a_{i2}	26.96539	q_{i1} =1.061354	-7.3732	q_{i1} =1.06892
m_{i1}	0.783307	q_{i2} =0.061354	-11.0395	q_{i2} =0.062561
m_{i2}	-0.21669	-	-23.8409	-

Table-2.b

Estimated Values Of The Parameters For EAGLE Image Number of Image Regions (K =3)						
Parameters	Estimation of Initial Parameters			Estimation of Final Parameters by EM Algorithm		
	Image Region			Image Region		
	1-TYPEI	2-TYPEVI	3-TYPEI	1-TYPEI	2-TYPEVI	3-TYPEI
α_i	0.333	0.333	0.333	0.950792	0.00245	0.046758
a_{i1}	-42.6351	a_i =-829.883	-35.4287	0.004741	a_i =-4.01E-12	-1.2948
a_{i2}	38.46268	q_{i1} =1.027226	38.6806	-0.1653	q_{i1} =1.028736	14.15414
m_{i1}	0.525725	q_{i2} =0.027226	0.47806	0.225525	q_{i2} =0.027134	2.642036
m_{i2}	-0.47428	-	-0.52194	0.594823	-	0.405279

Table-2.c

Estimated Values Of The Parameters For NEST BIRD Image Number of Image Regions (K =4)								
Parameters	Estimation of Initial Parameters				Estimation of Final Parameters by EM Algorithm			
	Image Region				Image Region			
	1-TYPEI	2-TYPEVI	3-TYPEI	4-TYPEI	1-TYPEI	2-TYPEVI	3-TYPEI	4-TYPEI
α_i	0.250	0.250	0.250	0.250	-0.03459	0.002342	0.650132	0.382119
a_{i1}	-24.3208	a_i =181.3095	-15.9394	-30.2968	-1.38028	a_i =1	-0.215	-0.26305
a_{i2}	28.31176	q_{i1} =1.066072	11.42341	14.58499	12.98182	q_{i1} =1.073076	-0.19938	-0.68031
m_{i1}	0.462087	q_{i2} =0.066072	0.582521	0.675036	0.297129	q_{i2} =0.06951	2.420679	2.281604
m_{i2}	-0.53791	-	-0.41748	-0.32496	0.848453	-	0.469579	0.520931

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Table-2.d

Estimated Values Of The Parameters For FACE Image Number of Image Regions (K =4)								
Parameters	Estimation of Initial Parameters				Estimation of Final Parameters by EM Algorithm			
	Image Region				Image Region			
	1-TYPEI	2-TYPEI	3-TYPEVI	4-TYPEI	1-TYPEI	2-TYPEI	3-TYPEVI	4-TYPEI
α_i	0.250	0.250	0.250	0.250	0.0068	0.9772	0.0078	0.0082
a_{i1}	-18.965	-24.176	a_i = -468.346	-16.528	20.6072	-0.1116	a_i =1.000	-2.290
a_{i2}	22.946	17.734	q_{i1} = 1.047	18.557	493.753	-0.3840	q_{i1} =-1.055	15.577
m_{i1}	0.4525	0.5768	q_{i2} = 0.0471	0.4710	-0.0283	2.4305	q_{i2} =0.0475	2.664
m_{i2}	-0.5474	-0.423	-	-0.5289	-0.0819	0.4662	-	0.3995

The probability density function of pixel intensities of each image is estimated by substituting the final estimates of the model parameters. The estimated probability density function of the pixel intensities of the image TIGER is

$$f(z_s,\theta^{(l)}) = \frac{(0.988622)(-0.00316)^{(-11.04)}(-7.37)^{(-23.84)}\left(1+\frac{z_i}{-0.0032}\right)^{-11.04}\left(1-\frac{z_i}{-7.373}\right)^{-23.84}}{(-0.00316-7.3732)^{(-11.0395+-23.8409+1)}\beta(-11.0395+1,-23.841+1)} + \frac{(0.011378)\left(z_s-1.000\right)^{0.062561}\left(z_s\right)^{-1.06892}}{(1.000)^{(0.0626-1.06892+1)}\beta(1.06892-0.06256-1,0.0626+1)}$$

The estimated probability density function of the pixelintensities of the image EAGLE is

$$f\left(z_s,\theta^{(l)}\right) = \frac{(0.950792)(0.005)^{(0.226)}(-0.1653)^{(0.5948)}\left(1+\frac{z_i}{0.005}\right)^{(0.226)}\left(1-\frac{z_i}{-0.1653}\right)^{(0.595)}}{(0.0047+-0.1653)^{(0.2255+0.5948+1)}\beta(0.225525+1,0.5948+1)} + \frac{(0.00245)\left(z_s-4.01E-12\right)^{0.062561}\left(z_s\right)^{1.028736}}{(4.01E-12)^{(0.027134-1.028736+1)}\beta(1.028736-0.027134-1,0.02713+1)} + \frac{(0.046758)(1.2948)^{(2.64204)}(14.154)^{(0.41)}\left(1+\frac{z_i}{1.2948}\right)^{(2.6421)}\left(1-\frac{z_i}{14.154}\right)^{(0.41)}}{(1.2948+14.154)^{(2.642036+0.405279+1)}\beta(2.642036+1,0.4053+1)}$$

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

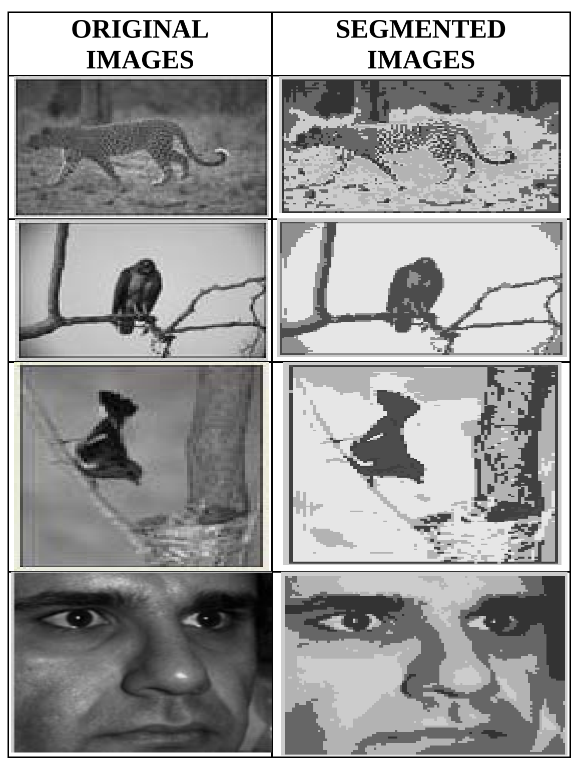
$$f\left(z_s,\theta^{(l)}\right) = \frac{(-0.03459)(-1.38)^{(0.29713)}(12.982)^{(0.8485)}\left(1+\frac{z_i}{-1.381}\right)^{(0.2971)}\left(1-\frac{z_i}{12.982}\right)^{(0.849)}}{(-1.38028+12.98182)^{(0.29713+0.8485+1)}\beta(0.2972+1,0.849+1)} + \frac{(0.002342)\left(z_s-1.000\right)^{0.06951}\left(z_s\right)^{1.073076}}{(1.000)^{(0.06951-1.073076+1)}\beta(0.06951-0.062561-1,0.06951+1)} + \frac{(0.650132)(-0.215)^{(2.421)}(-0.1994)^{(0.4696)}\left(1+\frac{z_i}{-0.215}\right)^{(2.4207)}\left(1-\frac{z_i}{-0.1994}\right)^{(0.469)}}{(-0.215-0.19938)^{(2.420679+0.4696+1)}\beta(2.420679+1,0.4696+1)} + \frac{(0.382119)(-0.2631)^{(2.282)}(-0.680)^{(0.521)}\left(1+\frac{z_i}{-0.263}\right)^{(2.282)}\left(1-\frac{z_i}{-0.68031}\right)^{(0.521)}}{(-0.26305-0.68031)^{(2.281604+0.520931+1)}\beta(2.281604+1,0.5209+1)}$$

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

$$f\left(z_s,\theta^{(l)}\right) = \frac{(0.0068)(20.61)^{(-0.0283)}(493.75)^{(-0.0819)}\left(1+\frac{z_i}{20.607}\right)^{(-0.028)}\left(1-\frac{z_i}{493.75}\right)^{(-0.082)}}{(20.6072+493.753)^{(-0.0283-0.0819+1)}\beta(-0.0283+1,-0.082+1)} + \frac{(0.9772)(-0.1116)^{(2.4305)}(-0.3840)^{(0.47)}\left(1+\frac{z_i}{-0.1116}\right)^{(2.431)}\left(1-\frac{z_i}{-0.384}\right)^{(0.47)}}{(-0.1116-0.3840)^{(2.4305+0.4662+1)}\beta(2.4305+1,0.4662+1)} + \frac{(0.0078)\left(z_s-1.000\right)^{0.0475}\left(z_s\right)^{1.055}}{(1.000)^{(0.0475-1.055+1)}\beta(1.055-0.0475-1,0.0475+1)} + \frac{(0.0082)(-2.29)^{(2.664)}(15.58)^{(0.3995)}\left(1+\frac{z_i}{-2.290}\right)^{(2.664)}\left(1-\frac{z_i}{15.58}\right)^{(0.3995)}}{(-2.290+15.58)^{(2.664+0.3995+1)}\beta(2.664+1,0.3995+1)}$$

Using the estimated probability density function and image segmentation algorithm given in section III, the image segmentation is done for the five images under consideration. The original and segmented images are shown in Figure 2

Figure 2 : Original and Segmented Images



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VII. Initialization of Parameters by Hierarchical Clustering Algorithm

In this section, we evaluate the efficiency of the proposed image segmentation algorithm. For this purpose of evaluation the images are collected from the Berkeley image data set. For this we need to randomly pick four images from the database and feature vector consisting of gray value for each pixel of the image. The feature vector in each image is modeled by using Pearsonian Type VI & Pearsonian Type I Distribution. By dividing all the pixel into different regions using Hierarchical Clustering Algorithm, the initial values of model parameters mi1, mi2, qi1,qi2 and αi are obtained. Using these values and the updated equations of EM- Algorithm discussed in section III with MATLAB code, the final values of the model parameters are calculated and presented in the tables 3.a, 3.b, 3.c and 3.d

Table-3.a

Estimated Values Of The Parameters For TIGER Image Number of Image Regions (K =2)				
Parameters	Estimation of Initial Parameters by Hierarchical clustering		Estimation of Final Parameters by EM Algorithm	
	Image Region		Image Region	
	1	2	1	2
α_i	0.500	0.500	2.01257	-1.01257
a_{i1}	-75.717	-11.7563	-1.6508	-0.0459
a_{i2}	82.970	740.670	88.3755	-28057.91
m_{i1}	0.4771	0.0156	0.6101	40.2429
m_{i2}	-0.5228	-0.9843	1.7071	0.01562

Table-3.b

Estimated Values Of The Parameters For EAGLE Image Number of Image Regions (K =3)						
Parameters	Estimation of Initial Parameters by Hierarchical clustering			Estimation of Final Parameters by EM Algorithm		
	Image Region			Image Region		
	1	2	3	1	2	3
α_i	0.333	0.333	0.333	0.4574	0.1921	0.3503
a_{i1}	-29.580	-99.0809	-41.2789	-0.1968	0.6095	-0.05994
a_{i2}	22.567	14.1523	35.7243	-0.7845	-0.70016	-1.0802
m_{i1}	0.5672	0.87501	0.53606	0.26831	2.08306	2.50880
m_{i2}	-0.4327	-0.1249	-0.4639	0.67742	0.61615	0.44170

Table-3.c

Estimated Values Of The Parameters For NEST BIRD Image Number of Image Regions (K =4)								
Parameters	Estimation of Initial Parameters by Hierarchical clustering				Estimation of Final Parameters by EM Algorithm			
	Image Region				Image Region			
	1	2	3	4	1	2	3	4
α_i	0.250	0.250	0.250	0.25	0.8124	0.6205	-0.1252	-0.3077
a_{i1}	-29.742	-42.662	-22.721	-13.326	-0.39174	-0.2174	-0.5579	-0.0467
a_{i2}	22.299	18.108	27.072	75.188	-0.8320	-0.7572	17.451	1018.7
m_{i1}	0.5715	0.7020	0.4563	0.1506	0.31705	2.2480	2.7025	5.3865
m_{i2}	-0.4284	-0.2979	-0.5436	-0.8494	0.7971	0.5349	0.3905	0.14647

Table-3.d

Estimated Values Of The Parameters For FACE Image Number of Image Regions (K =4)								
Parameters	Estimation of Initial Parameters by Hierarchical clustering				Estimation of Final Parameters by EM Algorithm			
	Image Region				Image Region			
	1	2	3	4	1	2	3	4
α_i	0.250	0.250	0.250	0.250	0.3736	0.2847	0.2526	0.0891
a_{i1}	-12.244	-12.556	-14.509	-68.801	-0.0611	-0.1155	-0.0811	1.5517
a_{i2}	71.505	11.0781	9.1209	57.659	2536.35	0.3296	0.1468	-5.4401
m_{i1}	0.1462	0.5312	0.6140	0.544	-0.3232	2.5188	2.3684	2.4925
m_{i2}	- 0.8537	-0.4687	-0.3859	-0.4559	-2.3224	0.4387	0.4876	0.4465

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

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

$$f\left(z_s,\theta^{(l)}\right)=\frac{(2.01257)(-1.6508)^{(0.6101)}(88.3755)^{(1.7071)}\left(1+\frac{z_i}{-1.6508}\right)^{(0.6101)}\left(1-\frac{z_i}{88.3755}\right)^{(1.7071)}}{(-1.6508+88.3755)^{(0.6101+1.7071+1)}\beta(0.6101+1,1.7071+1)}+\frac{(-1.01257)(-0.0459)^{(40.2429)}(-28057.91)^{(0.01562)}\left(1+\frac{z_i}{-0.0459}\right)^{(40.2429)}\left(1-\frac{z_i}{-28057.91}\right)^{(0.01562)}}{(-0.0459+-28057.91)^{(40.2429+0.01562+1)}\beta(40.2429+1,0.01562+1)}$$

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

$$f\left(z_s,\theta^{(l)}\right)=\frac{(0.4574)(-0.1968)^{(0.2683)}(-0.7845)^{(0.6774)}\left(1+\frac{z_i}{-0.1968}\right)^{(0.2683)}\left(1-\frac{z_i}{-0.7845}\right)^{(0.6774)}}{(-0.1968+-0.7845)^{(0.26831+0.6774+1)}\beta(0.26831+1,0.6774+1)}+\frac{(0.1921)(0.6095)^{(2.0831)}(-0.70016)^{(0.6162)}\left(1+\frac{z_i}{0.6095}\right)^{(2.0831)}\left(1-\frac{z_i}{-0.70016}\right)^{(0.6162)}}{(0.6095+-0.70016)^{(2.08306+0.61615+1)}\beta(2.08306+1,0.6162+1)}+\frac{(0.3503)(-0.05994)^{(2.5088)}(-1.0802)^{(0.442)}\left(1+\frac{z_i}{-0.05994}\right)^{(2.5088)}\left(1-\frac{z_i}{-1.0802}\right)^{(0.4417)}}{(-0.05994+-1.0802)^{(2.5088+0.4417+1)}\beta(2.5088+1,0.4417+1)}$$

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

$$f\left(z_s,\theta^{(l)}\right)=\frac{(0.8124)(-0.39174)^{(0.31705)}(-0.8320)^{(0.7971)}\left(1+\frac{z_i}{-0.39174}\right)^{(0.31705)}\left(1-\frac{z_i}{-0.8320}\right)^{(0.7971)}}{(-0.39174+-0.8320)^{(0.31705+0.7971+1)}\beta(0.31705+1,0.7971+1)}+\frac{(0.6205)(-0.2174)^{(2.2480)}(-0.7572)^{(0.5349)}\left(1+\frac{z_i}{-0.2174}\right)^{(2.2480)}\left(1-\frac{z_i}{-0.7572}\right)^{(0.5349)}}{(-0.2174+-0.7572)^{(2.2480+0.5349+1)}\beta(2.2480+1,0.5349+1)}+\frac{(-0.1252)(-0.5579)^{(2.7025)}(17.4509)^{(0.39047)}\left(1+\frac{z_i}{-0.5579}\right)^{(2.7025)}\left(1-\frac{z_i}{17.4509}\right)^{(0.39047)}}{(-0.5579+17.4509)^{(2.7025+0.39047+1)}\beta(2.7025+1,0.39047+1)}+\frac{(-0.30771)(-0.04669)^{(5.3865)}(1018.7)^{(0.14647)}\left(1+\frac{z_i}{-0.04669}\right)^{(5.3865)}\left(1-\frac{z_i}{1018.7}\right)^{(0.14647)}}{(-0.04669+1018.7)^{(5.3865+0.14647+1)}\beta(5.3865+1,0.14647+1)}$$

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

$$f\left(z_s,\theta^{(l)}\right)=\frac{(-0.6508)(-0.2402)^{(4.1042)}(1504.84)^{(13.844)}\left(1+\frac{z_i}{-0.2402}\right)^{(4.1042)}\left(1-\frac{z_i}{1504.84}\right)^{(13.844)}}{(-0.2402+1504.84)^{(4.1042+13.844+1)}\beta(4.1042+1,13.844+1)}+\frac{(-0.2327)(-0.1752)^{(2.9874)}(-622.13)^{(0.3331)}\left(1+\frac{z_i}{-0.1752}\right)^{(2.9874)}\left(1-\frac{z_i}{-622.13}\right)^{(0.3331)}}{(-0.1752+-622.13)^{(2.9874+0.3331+1)}\beta(2.9874+1,0.3331+1)}+\frac{(0.7248)(-96.5481)^{(2.3041)}(-5.9734)^{(0.51185)}\left(1+\frac{z_i}{-96.5481}\right)^{(2.3041)}\left(1-\frac{z_i}{-5.9734}\right)^{(0.51185)}}{(-96.5481+-5.9734)^{(2.3041+0.51185+1)}\beta(2.3041+1,0.51185+1)}+\frac{(1.1587)(-0.3530)^{(2.34037)}(-0.7436)^{(0.4979)}\left(1+\frac{z_i}{-0.3530}\right)^{(2.34037)}\left(1-\frac{z_i}{-0.7436}\right)^{(0.4979)}}{(-0.3530+-0.7436)^{(2.34037+0.4979+1)}\beta(2.34037+1,0.4979+1)}$$

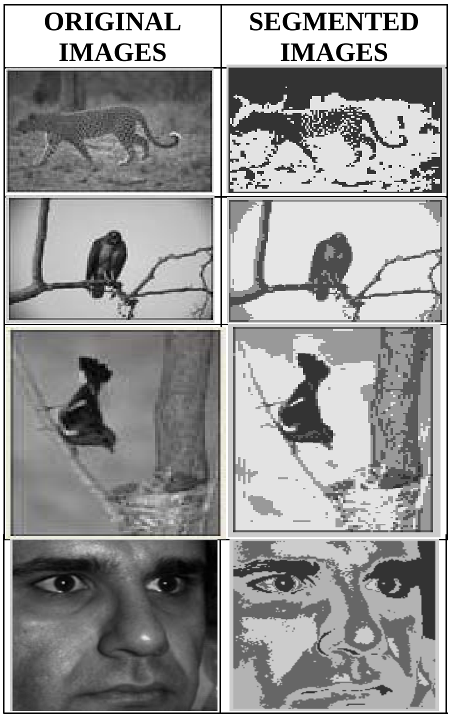
$$f\left(z_s,\theta^{(l)}\right)=\frac{(-0.6508)(-0.2402)^{(4.1042)}(1504.84)^{(13.844)}\left(1+\frac{z_i}{-0.2402}\right)^{(4.1042)}\left(1-\frac{z_i}{1504.84}\right)^{(13.844)}}{(-0.2402+1504.84)^{(4.1042+13.844+1)}\beta(4.1042+1,13.844+1)}+\frac{(-0.2327)(-0.1752)^{(2.9874)}(-622.13)^{(0.3331)}\left(1+\frac{z_i}{-0.1752}\right)^{(2.9874)}\left(1-\frac{z_i}{-622.13}\right)^{(0.3331)}}{(-0.1752+-622.13)^{(2.9874+0.3331+1)}\beta(2.9874+1,0.3331+1)}+\frac{(0.7248)(-96.5481)^{(2.3041)}(-5.9734)^{(0.51185)}\left(1+\frac{z_i}{-96.5481}\right)^{(2.3041)}\left(1-\frac{z_i}{-5.9734}\right)^{(0.51185)}}{(-96.5481+-5.9734)^{(2.3041+0.51185+1)}\beta(2.3041+1,0.51185+1)}+\frac{(1.1587)(-0.3530)^{(2.34037)}(-0.7436)^{(0.4979)}\left(1+\frac{z_i}{-0.3530}\right)^{(2.34037)}\left(1-\frac{z_i}{-0.7436}\right)^{(0.4979)}}{(-0.3530+-0.7436)^{(2.34037+0.4979+1)}\beta(2.34037+1,0.4979+1)}$$

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

$$f\left(z_s,\theta^{(l)}\right)=\frac{(0.3736)(-0.0611)^{(-0.3232)}(2536.35)^{(1.0010)}\left(1+\frac{z_i}{-0.0611}\right)^{(-0.3232)}\left(1-\frac{z_i}{2536.35}\right)^{(1.0010)}}{(-0.0611+2536.35)^{(-0.3232+1.0010+1)}\beta(-0.3232+1,1.0010+1)}+\frac{(0.2847)(-0.1155)^{(2.5188)}(0.3296)^{(0.4387)}\left(1+\frac{z_i}{-0.1155}\right)^{(2.5188)}\left(1-\frac{z_i}{0.3296}\right)^{(0.4387)}}{(-0.1155+0.3296)^{(2.5188+0.4387+1)}\beta(2.5188+1,0.4387+1)}+\frac{(0.2526)(-0.0811)^{(2.3684)}(0.1468)^{(0.4876)}\left(1+\frac{z_i}{-0.0811}\right)^{(2.3684)}\left(1-\frac{z_i}{0.1468}\right)^{(0.4876)}}{(-0.0811+0.1468)^{(2.3684+0.4876+1)}\beta(2.3684+1,0.4876+1)}+\frac{(0.0891)(1.5517)^{(2.4925)}(-5.4401)^{(0.4465)}\left(1+\frac{z_i}{1.5517}\right)^{(2.4925)}\left(1-\frac{z_i}{-5.4401}\right)^{(0.4465)}}{(1.5517+-5.4401)^{(2.4925+0.4465+1)}\beta(2.4925+1,0.4465+1)}$$

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

Figure 3 : Original and Segmented Images



VIII. Performance Evalution

In this paper we have conducted the experiment and also examined its performance by making use of the image segmentation algorithm. The performance evaluation of this segmentation technique is carried by obtaining the three performance measures namely, (i) probabilistic rand index (PRI), (ii) global consistence error (GCE) and (iii) variation of information (VOI). By computing the segmentation performance measures namely VOI, PRI and GCE for the five images under study using Pearsonian Type VI Distribution (PTVID-K), the performance of the developed algorithm is studied. The computed values of the performance measures for the developed algorithm and the earlier existing finite Gaussian mixture model(GMM) with K-means algorithm and Hierarchical algorithm are presented in Table 4 for a comparative study.

Table 4 : Segmentation Performace Measures

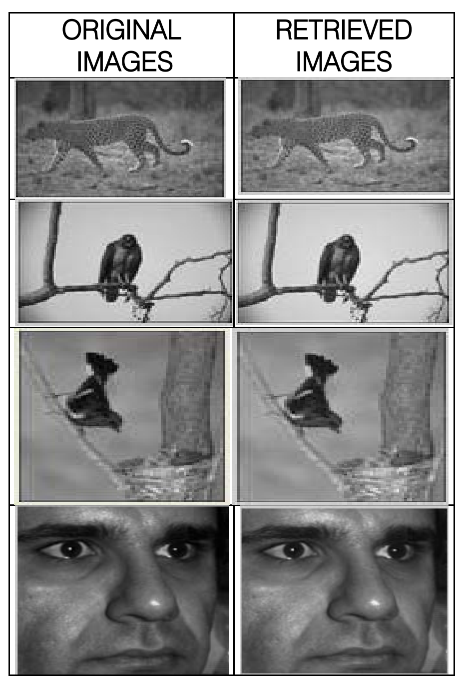
IMAGES	METHOD	PERFORMACE MEASURES		
		PRI	GCE	VOI
TIGER	GMM	0.8234	0.4956	2.568
	PTVID-K	0.9896	0.4742	1.921
	PTVID-H	0.9897	0.4762	1.920
EAGLE	GMM	0.8423	0.7006	8.354
	PTVID-K	0.8505	0.7109	7.577
	PTVID-H	0.8627	0.7054	7.2002
NEST BIRD	GMM	0.9793	0.9142	8.8837
	PTVID-K	0.0258	0.0124	6.7136
	PTVID-H	0.0074	0.0001	7.2132
FACE	GMM	0.0201	0.0891	7.2546
	PTVID-K	0.0223	0.0134	7.1556
	PTID-K	0.9559	0.8584	8.8772

From Table 4 it is identified that the PRI values of the existing algorithm based on finite Gaussian Mixture model for the five images considered for experimentation are less than the values from the segmentation algorithm based Pearsonian Type VI Distribution with K-means. Similarly GCE and VOI values of the proposed algorithm are less than that of finite Gaussian mixture model. This reveals the fact that the proposed algorithm outperforms the existing algorithm based on the finite Gaussian mixture model.

After developing the image segmentation method , it is required to verify the utility of segmentation in model building of the image for image retrieval. By subjective image quality testing or by objective image quality testing the performance evaluation of the retrieved image can be done. Since the numerical results of an objective measure allow a consistent comparison of different algorithms the objective image quality testing methods are often used. 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).

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



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For the above retrieved images FACE, NEST BIRD AND EAGLE The calculated image quality measures using proposed PTVID and GMM with K-means and Hierarchical algorithm are displayed in the Table 5.

Table 5 : Comparative Study of Image Quality Metrics

IMAGE	Quality Metrics	GMM	PTVID -K	PTVID- H	Standard Limits
TIGER	Average Difference	0.4837	0.4203	0.4193	Close to 0
	Maximum Distance	1.0000	1.000	1.0000	Close to 1
	Image Fidelity	1.0000	1.0000	0.99996	Close to 1
	Mean Square Error	0.6011	0.4103	0.4100	Close to 0
	Signal to Noise Ratio	6.6542	6.0885	6.6416	As big as possible
	Image Quality Index	1.0000	1.0025	1.0025	Close to 1
EAGLE	Average Difference	0.5946	0.5141	0.4538	Close to 0
	Maximum Distance	1.0000	1.0000	1.0000	Close to 1
	Image Fidelity	1.0000	0.9717	0.8628	Close to 1
	Mean Square Error	0.4946	0.3487	0.2367	Close to 0
	Signal to Noise Ratio	5.6828	11.1517	15.1083	As big as possible
	Image Quality Index	1.0000	0.9051	0.673046	Close to 1
NEST BIRD	Average Difference	0.4930	0.4094	0.3773	Close to 0
	Maximum Distance	1.0000	1.0000	1.0000	Close to 1
	Image Fidelity	1.0000	0.9136	0.856846	Close to 1
	Mean Square Error	0.4930	0.4453	0.3783	Close to 0
	Signal to Noise Ratio	5.6897	13.8803	14.1535	As big as possible
	Image Quality Index	1.0011	0.7311	0.571059	Close to 1
FACE	Average Difference	0.579	0.3170	0.2217	Close to 0
	Maximum Distance	1.0000	1.0000	1.0000	Close to 1
	Image Fidelity	1.0000	0.5703	0.6804	Close to 1
	Mean Square Error	0.5079	0.4556	0.1652	Close to 0
	Signal to Noise Ratio	5.6251	19.6707	20.7562	As big as possible
	Image Quality Index	1.0007	0.0366	0.0336	Close to 1

It is perceived that all the image quality measures for the five images are meeting the standard criteria as given in the Table 5. Basing on the above mentioned quality metrics we can retrieve images accurately by using the proposed algorithm. A comparative study is done on the algorithm based on finite Gaussian mixture model with the proposed algorithm and it reveals that the MSE of the proposed model is less than that of the finite Gaussian mixture model. The performance of the proposed model in retrieving the images is better than the finite Gaussian mixture model by making use of these quality metrics.

IX. Conclusion

In this paper, by using finite mixture of Pearsonian Type VI distribution a new model image segmentation is introduced and analyzed. The pixel intensities of animal images better characterizes the mixture of Pearsonian Type VI distribution which is validated through experiment with Berkeley image data set. The model parameters are estimated by using the EM Algorithm. By using the Maximum Likelihood estimates, the Segmentation Algorithm is developed under Bayesian framework. The Experiment on the Berkeley image data set reveals that this image segmentation method outperforms in segmenting the animal images then that of the existing algorithm basing on Gaussian mixture model with respect to image segmentation quality metrics such as PRI, GCE and VOI. The proposed algorithm is much useful for image analysis and image retrievals. The image that is developed can be extended with a K-dimensional feature vector for color images which will be takes as elsewhere.

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