International Journal of Grid and Distributed Computing
Vol. 11, No. 12 (2018), pp.1-20
http://dx.doi.org/10.14257/ijgdc.2018.11.12.01

Segmentation of Images Using Two Parameter Logistic Type Distribution and K-Means Clustering

K. Srinivasa Rao[1], K.V. Satyanarayana[2] and P. Srinivasa Rao[3]

[1]Department of Statistics,
Andhra University, Visakhapatnam, India
[2]Department of CSE,
Avanthi Institute of Engg. and Technology, Visakhapatnam, India
[3]Department of CSSE,
Andhra University, Visakhapatnam, India
ksraoau@yahoo.co.in, vsatyanarayana.kalahasthi@gmail.com,
peri.srinivasarao@yahoo.com

Abstract

The current article deal with the utilization of two parameters logistic type distribution in image segmentation and image retrivals. The proposed algorithm is having application in medical diagnostics, security and surveillance analysis, remote sensing etc. This algorithm serves as a generalization of the image segmentation with Gaussian mixture models since the two parameter logistic type distribution is capable of including platy kurtic and mesokurtic distributions as particular cases. In this paper we assume that the pixel intensity of whole image is characterized by mixture of two parameters logistic type distribution. The model parameters are assessed utilizing EM-calculation. The introduction of parameters is finished with k-implies calculation and minute technique for estimation. The execution of the created calculation is considered through directing experimentation with five pictures arbitrarily taken from Berkeley-picture database and utilizing the division measurements PRI, GCE, VOI. It is observed that this algorithm outperforms the existing algorithm in segmenting for the images, which have platy kurtic distribution of pixel intensities.

Keywords*: Image segmentation, two parameter logistic type distribution, EM-algorithm, performance evaluation*

1. Introduction

For image processing and analysis, image segmentation is a prime consideration. In segmentation we separate the objects of interest in the image, which characterize the process of dividing the picture into homogenous image regions. In the model based segmentation method, the entire picture is distinguished by a combination of likelihood distributions. The pixel strength is measured as a characteristic for image segmentation. The pixel intensities in an image region may be distributed as platykurtic and laptokurtic, and mesokurtic. Because of effortlessness and computational comfort, picture division calculations in view of Gaussian blend models were produced [2,3]. Anyway in Gaussian blend models the pixel powers in picture area are meso kurtic. Henceforth, to have a nearby guess to the pixel densities, it is expected to consider another option to the Gaussian circulation which is symmetric. Seshashayee *et al.*, (2011), Jyothirmayi *et al.*, (2016), (2017), Srinivara Rao *et al.*, (2011), have built up some picture division strategies in view of New Symmetric Mixture models, and blend of summed up Laplace models.

Received (September 8, 2018), Review Result (November 7, 2018), Accepted (December 6, 2018)

ISSN: 2005-4262 IJGDC

Recently Srinivara Rao *et al.*, (2018) have commenced a logistic type distribution which is very useful in portraying symmetric and platykurtic distributions. No related work had observed in the literature for utilizing the usage of two parameter logistic type distribution in image segmentation.

The remaining paper is prepared as follows: in section-2, the combination of two parameter logistic type allocation and its possessions are confer in section-3, the assessment of the replica constraints using EM-algorithm is deliberated in section-4 is discussed. The segmentation algorithm using maximum likely hood under the Bayesian frame is presented in Section 5. In Section 6 The performance of the considered algorithm is studied by experimentation with five images randomly taken from Berkeley image database and presentation measure such as PRI, GCE, VOI are computed. In Section 7 a comparative study of developed algorithm with that of existing algorithms is presented. Section 8 deals with conclusions.

2. Two Parameter Logistic Type Distribution

In this section, we briefly present the mixture of two parameter logistic type distribution. For a given pixel at (x y), the pixel intensity $z = f(x, y)$ is an irregular variable in view of the way that the shine estimated at a point in the picture is affected by different arbitrary components like vision, lighting, dampness, ecological conditions and so forth.,. To demonstrate the pixel powers of the picture locale it is accepted that the pixel powers of the picture district take after a two parameter calculated compose appropriation given by Srinivasa Rao K, *et al.*, (2018).

The pixel intensity which can be represented by the function as,

$$f(x,\mu,\sigma^2) = \frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x-\mu}{\sigma}\right)^2\right]e^{-\left(\frac{x-\mu}{\sigma}\right)}}{\sigma\left[1+e^{-\left(\frac{x-\mu}{\sigma}\right)^2}\right]}, -\infty < x < \infty, -\infty < \mu < \infty, \sigma > 0 \quad (1)$$

Two parameter logistic type distributions which can be represented by the frequency curve associated is shown in Figure 1.

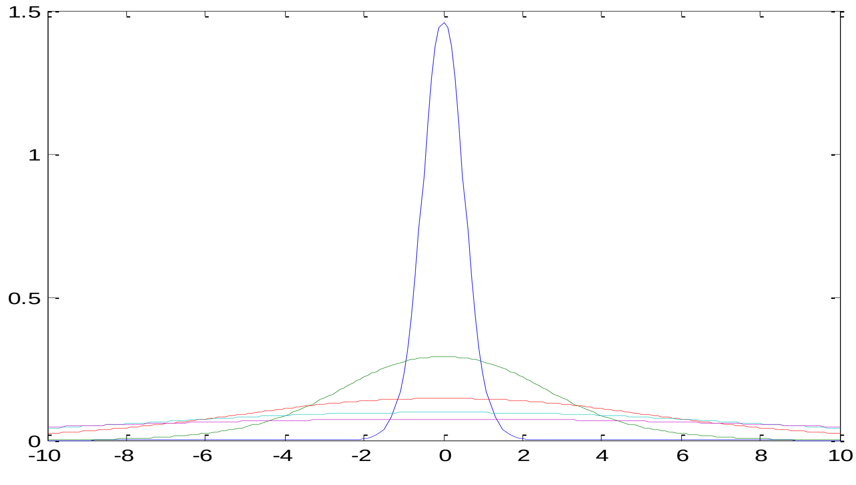


Figure 1. Frequency Curve of Two Parameter Logistic Type Distribution

The distribution is symmetric about μ and the distribution function

$$F(X)=\frac{3e^{-\left(\frac{x-\mu}{\sigma}\right)}}{\sigma^2(12+\pi^2)}\frac{\left[\left[4+\left(\frac{x-\mu}{\sigma}\right)^2\right]\left[2\left(\frac{x-\mu}{\sigma}\right)-1\right]e^{-\left(\frac{x-\mu}{\sigma}\right)^2}-\left[\left(\frac{x-\mu}{\sigma}\right)-1\right]^2\right]}{\left[1+e^{-\left(\frac{x-\mu}{\sigma}\right)^2}\right]^2}$$

The actual image is full of group of regions which were distinguished by two parameter logistic type distribution. Hence, it is understood that the pixel intensities of the entire image trails k-component mixture of two parameter logistic type distribution as,

$$p(x)=\sum_{i=1}^{k}\alpha_i f_i(x,\mu,\sigma^2) \qquad (2)$$

Where k is the number of regions $0\le\alpha_i\le1$ are weights such that $\sum\alpha_i=1$ and $f_i(x,\mu,\sigma^2)$ is given in equation (1). α_i is the weight associated with i[th] region in the whole image.

Once the correlation is reduced, the pixels can be considered to be as independent and uncorrelated. The entire intensity of the whole image is considered as,

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

3. Evaluation of the Parameters considered in the model by using EM Algorithm:-

The parameters of the current model considered in the article are estimated by means of likelihood function of the sample observations. For this distribution, the likelihood equation is nonlinear and there is no solution by analytic means. Consequently, we use some iterative procedure like EM algorithm for obtaining the estimates of the parameters.

The probability of the function of model is

$$L(\theta)=\prod_{S=1}^{N}p(x_s,\theta^{(l)}) \qquad (3)$$

$$L(\theta)=\prod_{s=1}^{N}\left(\sum_{i=1}^{k}\alpha_i f_i(x_s,\theta^{(l)}\right) \qquad (4)$$

This implies

$$\log L(\theta)=\sum_{S=1}^{N}\log\left(\sum_{i=1}^{k}\alpha_i f_i(x_s,\theta^{(l)})\right)$$

Where $\theta=(\mu_i,\sigma_i^2,\alpha_i;i=1,2,\ldots\ldots\ldots\ldots k)$ is the set of parameter

Therefore

$$\log L(\theta)=\sum_{S=1}^{N}\log\left[\sum_{i=1}^{k}\alpha_i\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2\right]e^{-\left(\frac{x_s-\mu_i}{\sigma_i}\right)}}{\sigma_i\left[1+e^{-\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right]}\right] \qquad (5)$$

E-STEP:-

In the anticipation (E) step, the anticipation assessment of log $L(\theta)$ with esteem to the early limit vector $\theta^{(0)}$ is

$$Q(\theta,\theta^{(0)}) = E_{\theta^{(0)}}\left[\log L(\theta)/\bar{x}\right] \quad (6)$$

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

$$P(x_s,\theta^{(l)}) = \sum_{i=1}^{k} \alpha_i f_i(x_s,\theta^{(l)}) \quad (7)$$

$$L(\theta) = \prod_{s=1}^{N} p(x_s,\theta^{(l)}) \quad (8)$$

This implies

$$\log L(\theta) = \sum_{s=1}^{N} \log\left(\sum_{i=1}^{k} \alpha^{(l)}{}_i f_i(x_s,\theta^{(l)})\right) \quad (9)$$

The conditional probability of any observations x_s, belongs to any region 'k' is

$$P_k(x_s,\theta^{(l)}) = \left[\frac{\alpha_k{}^{(l)} f_k(x_s,\theta^{(l)})}{p_i(x_s,\theta^{(l)})}\right] \quad (10)$$

$$p_k(x_s,\theta^{(l)}) = \left[\frac{\alpha_k{}^{(l)} f_k(x_s,\theta^{(l)})}{\sum_{i=1}^{k} \alpha_i{}^{(l)} f_i(x_s,\theta^{(l)})}\right] \quad (11)$$

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

But we have

$$f_i(x_s,\theta^{(l)}) = \frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_s-\mu_i{}^{(l)}}{\sigma^{(l)}}\right)^2\right]e^{-\left(\frac{x_s-\mu_i{}^{(l)}}{\sigma_i{}^{(l)}}\right)}}{\sigma_i{}^{(l)}\left[1+e^{-\left(\frac{x_s-\mu_i{}^{(l)}}{\sigma_i{}^{(l)}}\right)^2}\right]} \quad (12)$$

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

$$Q(\theta,\theta^{(l)}) = \sum_{i=1}^{k}\sum_{s=1}^{N}\left(P_i(x_s,\theta^{(l)})(\log f_i(x_s,\theta^{(l)}) + \log \alpha_i{}^{(l)})\right) \quad (13)$$

M-STEP:-

For getting the estimation of replica restrictions one has to maximize $Q(\theta,\theta^{(l)})$ such that $\sum \alpha_i = 1$. This can be solved by pertaining the normal answer technique for forced most by building the primary arrange Lagrange kind task,

$$F = \left[E\left(\log L(\theta^{(l)})\right) + \lambda\left(1 - \sum_{i=1}^{k} \alpha_i{}^{(l)}\right)\right] \quad (14)$$

Where, λ is Lagrangian multiplier unite the limitation with the log likelihood function to be increased.

The Updated equations of α_i:

To find the expression for α_i, we solve the following equation

$$\frac{\partial F}{\partial \alpha_i} = 0$$

This implies

$$\frac{\partial}{\partial \alpha_i}\left[\sum_{i=1}^{N}\sum_{S=1}^{K} P_i(x_s,\theta^{(l)})\log\left[\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_s-\mu_i^{(l)}}{\sigma}\right)^2\right]e^{-\left(\frac{x_s-\mu_i^{(l)}}{\sigma_i^{(l)}}\right)}}{\sigma_i^{(l)}\left[1+e^{-\left(\frac{x_s-\mu_i^{(l)}}{\sigma_i^{(l)}}\right)^2}\right]}\right]+\log\alpha_i\right]+\lambda\left(1-\sum_{i=1}^{k}\alpha_i\right)=0 \quad (15)$$

This implies

$$\sum_{i=1}^{N}\frac{1}{\alpha_i}P_i(x_s,\theta^{(l)})+\lambda=0$$

Summing both sides over all observations, we get $\lambda=-N$

Therefore, $\alpha_i=\frac{1}{N}\sum_{s=1}^{N}P_i(x_s,\theta^{(l)})$

The updated equations of α_i for $(l+1)^{th}$ iteration is

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

This implies

$$\alpha_i^{(l+1)}=\frac{1}{N}\sum_{s=1}^{N}\left[\frac{\alpha_i^{(l)}f_i(x_s,\theta^{(l)})}{\sum_{i=1}^{k}\alpha_i^{(l)}f_i(x_s,\theta^{(l)})}\right] \quad (16)$$

3.1. The Updated equations of μ_i:

For updating the parameter $\mu_i, i=1,2,3.........k$ we consider the derivatives of $Q(\theta,\theta^{(l)})$ with respect to μ_i and equal to zero

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

There fore $\frac{\partial}{\partial\mu_i}(Q(\theta,\theta^{(l)}))=0$

Implies $E\left[\frac{\partial}{\partial\mu_i}(\log L(\theta,\theta^{(l)}))\right]=0$

Taking the partial derivative with respect to μ_i, we have

$$\frac{\partial}{\partial\mu_i}\left[\sum_{s=1}^{N}\sum_{i=1}^{K}P_i(x_s,\theta^{l})\log\alpha_i\frac{\left[\frac{3}{12+\pi^2}\right]\left[4+\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2\right]e^{-\left(\frac{x_s-\mu_i}{\sigma_i}\right)}}{\sigma_i\left[1+e^{-\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right]}\right]=0 \quad (17)$$

Since μ_i appears in only one region, i=1,2,3...........k (regions),
The above equation yields

$$\frac{\partial}{\partial\mu_i}\left[\sum_{s=1}^{N}\sum_{i=1}^{k}p_i(x_s,\theta^{l})\left[\log\left[\frac{3}{12+\pi^2}\right]+\log\left[4+\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2\right]-\left[\frac{x_s-\mu_i}{\sigma_i}\right]+\log\alpha_i-\log\sigma_i+\log\left[1+e^{-\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right]\right]\right]=0 \quad (18)$$

This implies

$$\sum_{s=1}^{N} P_i(x_s,\theta^l)\left[\left[\frac{2\left(\frac{x_s-\mu_i}{\sigma_i}\right)\left(-\frac{1}{\sigma_i}\right)}{\left[4+\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2\right]}\right]+\left[\frac{1}{\sigma_i}\right]-\left[\frac{e^{-\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}2}{\sigma_i\left(1+e^{-\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right]=0 \quad (19)$$

After Simplifying, we get

$$\sum_{s=1}^{N} P_i(x_s,\theta^l)\left[\frac{-2(x_s-\mu_i)}{\left(4\sigma_i^2+(x_s-\mu_i)^2\right)}+\left[\frac{1}{\sigma_i}\right]-\left[\frac{2}{\sigma_i^2\left(1+e^{\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right]=0$$

$$\sum_{s=1}^{N} P_i(x_s,\theta^l)\left[\left[\frac{-2x_s}{(4\sigma_i^2+(x_s-\mu_i)^2)}\right]+\left[\frac{2\mu_i}{(4\sigma_i^2+(x_s-\mu_i)^2}\right]+\left[\frac{1}{\sigma_i}\right]-\left[\frac{2}{\sigma_i\left(1+e^{\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right]=0 \quad (20)$$

Further simplification of above equations gives

$$\sum_{s=1}^{N} P_i(x_s,\theta^l)\left[\frac{2\mu_i}{\left(4\sigma_i^2+(x_s-\mu_i)^2\right)}\right]=\sum_{s=1}^{N} P_i(x_s,\theta^l)\left[\left[\frac{2x_s}{(4\sigma_i^2+(x_s-\mu_i)^2}\right]-\left[\frac{1}{\sigma_i}\right]+\left[\frac{2}{\sigma_i\left(e^{\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right] \quad (21)$$

We get

$$\mu_i=\frac{\sum_{s=1}^{N}\left[\left[\frac{2x_s}{\left(4\sigma_i^2+(x_s-\mu_i)^2\right)}\right]-\left[\frac{1}{\sigma_i}\right]+\left[\frac{2}{\sigma_i\left(1+e^{\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right]p_i(x_s,\theta^l)}{\sum\frac{2p_i(x_s,\theta^l)}{\left(4\sigma_i^2+(x_s-\mu_i)^2\right)}} \quad (22)$$

Therefore the updated equations of μ_i at $(l+1)^{th}$ iteration is

$$\mu_i^{(l+1)}=\frac{\sum_{s=1}^{N}\left[\left[\frac{2x_s}{\left(4\sigma_i^{2(l)}+(x_s-\mu_i^{(l)})^2\right)}\right]-\left[\frac{1}{\sigma_i^{(l)}}\right]+\left[\frac{2}{\sigma_i^{(l)}\left(1+e^{\left(\frac{x_s-\mu_i^{(l)}}{\sigma_i^{(l)}}\right)^2}\right)}\right]\right]p_i(x_s,\theta^{(l)})}{\sum\frac{2p_i(x_s,\theta^{(l)})}{\left(4\sigma_i^{2(l)}+(x_s-\mu_i^{(l)})^2\right)}} \quad (23)$$

The Updated Equation of σ_i^2 :

For updating σ_i^2 we differentiate $Q(\theta,\theta^{(l)})$ with respect to σ_i^2 and equate it to zero

That is $$\frac{\partial}{\partial\sigma^2}(Q(\theta,\theta^{(l)}))=0$$

This implies $$E\left[\frac{\partial}{\partial\sigma^2}(\log L(\theta,\theta^{(l)}))\right]=0$$

The above equation yields

$$\frac{\partial}{\partial \sigma_i^2}\left[\sum_{s=1}^{N}\sum_{i=1}^{k} p_i(x_s,\theta^l)\left[\log\left[\frac{3}{12+\pi^2}\right]+\log\left[4+\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2\right]-\left[\frac{x_s-\mu_i}{\sigma_i}\right]+\log\alpha_i-\log\sigma_i+\log\left[1+e^{-\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right]\right]\right]=0$$

This implies

$$\frac{\partial}{\partial \sigma_i^2}\left[\sum_{s=1}^{N}\sum_{i=1}^{k} p_i(x_s,\theta^l)\left[\log\left[\frac{3}{12+\pi^2}\right]+\log\left[4+\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2\right]-\left[\frac{x_s-\mu_i}{(\sigma_i^2)^{1/2}}\right]+\log\alpha_i-\frac{1}{2}\log\sigma_i^2+\log\left[1+e^{-\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right]\right]\right]=0 \qquad (25)$$

Simplifying the above equation we have

$$\sum_{s=1}^{N} p_i(x_s,\theta^{(l)})\left[\left[\frac{-\left(\frac{x_s-\mu_i}{\sigma_i^2}\right)^2}{\left(4+\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2\right)}\right]+\left[\left(\frac{x_s-\mu_i}{\sigma_i^3}\right)\right]-\left[\frac{1}{2\sigma_i^2}\right]-\left[\frac{e^{-\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\left[\frac{(x_s-\mu_i)^2}{\sigma_i^4}\right]}{\left(1+e^{-\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right]=0 \qquad (26)$$

This implies,

$$\sum_{s=1}^{N} p_i(x_s,\theta^{(l)})\left[\left[\frac{-(x_s-\mu_i)^2\sigma_i^2}{\sigma_i^4(4\sigma_i^2+(x_s-\mu_i)^2}\right]+\left[\frac{(x_s-\mu_i)}{\sigma_i^3}\right]-\left[\frac{1}{2\sigma_i^2}\right]-\left[\frac{(x_s-\mu_i)^2}{\sigma_i^4\left(1+e^{\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right]=0 \qquad (27)$$

This implies,

$$\sum_{s=1}^{N} p_i(x_s,\theta^{(l)})\left[\frac{-(x_s-\mu_i)^2\sigma_i^2}{\sigma_i^4(4\sigma_i^4+(x_s-\mu_i)^2}\right]=\sum_{s=1}^{N} p_i(x_s,\theta^l)\left[\left[\frac{-(x_s-\mu_i)}{\sigma_i^3}\right]+\left[\frac{1}{\sigma_i^2}\right]+\left[\frac{(x_s-\mu_i)^2}{\sigma_i^4\left(1+e^{\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right]=0$$

This implies,

$$\sum_{s=1}^{N} p_i(x_s,\theta^{(l)})\left[\frac{(x_s-\mu_i)^2\sigma_i^2}{\sigma_i^4(4\sigma_i^4+(x_s-\mu_i)^2}\right]=\sum_{s=1}^{N} p_i(x_s,\theta^l)\left[\left[\frac{(x_s-\mu_i)}{\sigma_i^3}\right]-\left[\frac{1}{\sigma_i^2}\right]-\left[\frac{(x_s-\mu_i)^2}{\sigma_i^4\left(1+e^{\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right]=0$$

(28)

After simplification the above equation can written as

$$\sigma_i^2 = \frac{\sum_{s=1}^{N}\left[\left[\frac{(x_s-\mu_i)}{\sigma_i^3}\right]-\left[\frac{1}{\sigma_i^2}\right]-\left[\frac{(x_s-\mu_i)^2}{\sigma_i^4\left(1+e^{\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right]p_i(x_s,\theta^{(l)})}{\sum_{s=1}^{N}\frac{(x_s-\mu_i)p_i(x_s,\theta^{(l)})}{\sigma_i^4(4\sigma_i^2+(x_s-\mu_i)^2)}} \quad (29)$$

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

$$\sigma_i^{2^{(l+1)}} = \frac{\sum_{s=1}^{N}\left[\left[\frac{(x_s-\mu_i^{(l+1)})}{\sigma_i^{3^{(l)}}}\right]-\left[\frac{1}{\sigma_i^{2^{(l)}}}\right]-\left[\frac{(x_s-\mu_i^{(l+1)})^2}{\sigma_i^4\left(1+e^{\left(\frac{x_s-\mu_i^{(l+1)}}{\sigma_i^{(l)}}\right)^2}\right)}\right]\right]p_i(x_s,\theta^{(l)})}{\sum_{s=1}^{N}\frac{(x_s-\mu_i^{(l+1)})p_i(x_s,\theta^{(l)})}{\sigma_i^{4^{(l)}}(4\sigma_i^{2^{(l)}}+(x_s-\mu_i^{(l+1)})^2)}} \quad (30)$$

Where,

$$p_i(x_s,\theta^{(l)}) = \left[\frac{\alpha_i^{(l+1)} f_i(x_s,\mu_i^{(l+1)},\sigma_i^{2^{(l)}})}{\sum_{i=1}^{k}\alpha_i^{(l+1)} f_i(x_s,\mu_i^{(l+1)},\sigma_i^{(l)})}\right] \quad (31)$$

4. Parameters Initialization by K-Means:

The competence of the EM algorithm in approximating the constraints is greatly reliant on the amount of sections in the picture. The quantity of blend segments taken for k-implies calculation is gotten, by plotting the histogram of the pixel powers of the entire picture, and the quantity of tops in the histogram can be taken as the underlying estimation of the quantity of areas k. The parameters α_i, μ and σ^2 are usually considered as known apriori.

To beat this issue, we utilize the k-implies calculation to isolate the entire picture into standardized districts. K-implies calculation utilizes an iterative system that limits the whole separations from each question its group centroid, over all bunches. This technique comprises of the accompanying advances.

1. Arbitrarily pick K information focuses from the dataset as beginning bunches. These information focuses speak to beginning group centroids.

2. Calculate Euclidian separation of every datum point from each bunch focus and allocate the information focuses to its closest group focus.

3. Calculate new bunch focus with the goal that squared blunder separation of each group ought to be least.

4. Repeat stage 2 and 3 until the point that grouping focuses don't change.

5. Stop the procedure.

In the above calculation the bunch focuses are just refreshed once the sum total of what indicates have been distributed their shut group focus. k-implies calculation relies upon the parameter k, the quantity of bunches in the picture. In the wake of deciding the last estimations of k(number of districts),we acquire the underlying assessments of and for the ith area utilizing the fragmented locale pixel forces with the technique given by Srinivasa Rao K, *et. al.*, (1997) for two parameter calculated circulation. The initial estimate as $\alpha_i = \frac{1}{k}$, where i=1, 2, 3……………..k. The parameter μ_i and σ_i^2 are expected by the process of moment as $\hat{\mu}_i = \bar{X}$ and $\sigma_i^2 = \frac{4n_i}{3(n_i - 1)}$ S^2, where S^2 is sample variance, n_i is the number of observations in the i^{th} segmentation.

4.1. Segmentation Algorithm

In this segment, we introduce the picture division calculation. Subsequent to refining the parameters, the prime advance in picture division on apportioning the pixels to the sections of the picture. This task is performed by division calculation. The picture division calculation comprises of four stages.

1. Plot the histogram of the whole image.
2. Achieve the initial estimates of the model parameters using K-means algorithm and moment estimates for each image region as discussed in Section 1.4.
3. Achieve the advanced estimation of the replica limits like μ_i, σ_i^2 and α_i for i=1,2,3……k, by utilizing the Expectation and Maximization algorithm with the efficient equations specified by (5),(7), and (8) respectively in Section 3.3.
4. Allocate every pixel into the equivalent j^{th} area according to the maximum likelihood of the j^{th} component L_j

That is

$$L_j = MAX\left[\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_s-\mu_j}{\sigma_j}\right)^2\right]e^{-\left(\frac{x_s-\mu_j}{\sigma_j}\right)}}{\sigma_j\left[1+e^{-\left(\frac{x_s-\mu_j}{\sigma_{j_i}}\right)^2}\right]}\right], -\infty < x_s < \infty, -\infty < \mu_j < \infty,$$

$$\sigma_j > 0$$

5. Experimentation and Results

The EM algorithm for model has been implemented in MATLAB and tested its efficiency for picture segmentation. To exhibit the usefulness of the picture division calculation built up, an examination is led with five pictures taken from Berkeley Images datasets. The pictures OSTRICH, WOMAN, OCEAN, HILLS, and EAGLE are considered for picture division. The pixel forces of the picture are accepted to take after a blend of two parameter strategic compose circulation. We consider that the picture contains k locales and pixel powers in each picture area take after a two parameter strategic compose dispersion with various parameters. The quantity of portions in every one of five pictures measured for testing is dictated by the histogram of pixel powers.

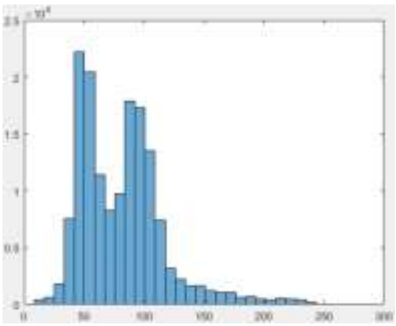
Table 5.1a: ML Estimates for Ostrich data for(K=2)

Parameters	Estimation of Initial Parameters		Estimation of final Parameters by EM Algorithm	
	Image Region		Image Region	
	1	2	1	2
α_i	0.500	0.500	0.9247	0.0753
μ_i	40.5146	113.260	74.8295	161.528
σ_i^2	64.09627	141.798	685.4975	1517.3920

Ostrich Grey image

Ostrich Segment 1

Ostrich Segment 2



Ostrich Histogram

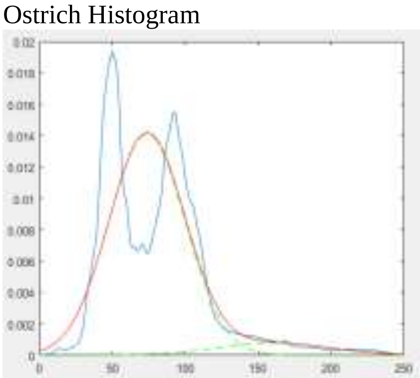


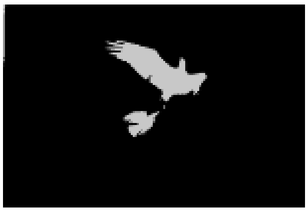
Figure 2. Plots of Ostrich Probability Density and TPLTM Estimated by EM

Table5.1b: ML Estimates for EAGLE data for (K=2)

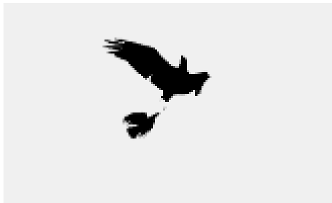
Parameters	Estimation of Initial Parameters		Estimation of Final Parameters by EM Algorithm	
	Image Region		Image Region	
	1	2	1	2
α_i	0.500	0.500	0.93890	0.06109
μ_i	40.5146	113.2603	113.2905	56.1087
σ_i^2	64.09627	141.798	129.8414	1143.5228

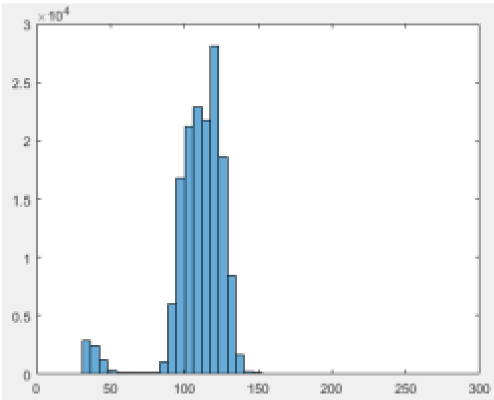
Eagle Gray Image

Eagle Segment 1



Eagle Segment2





Eagle Histogram

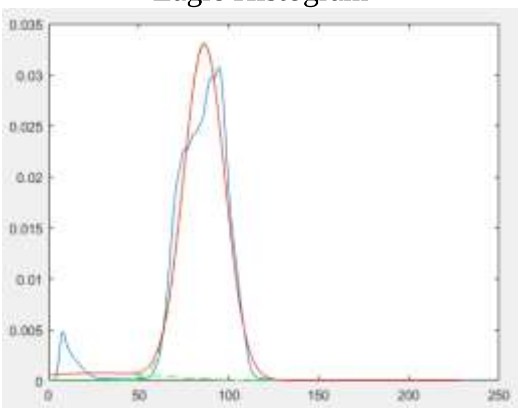
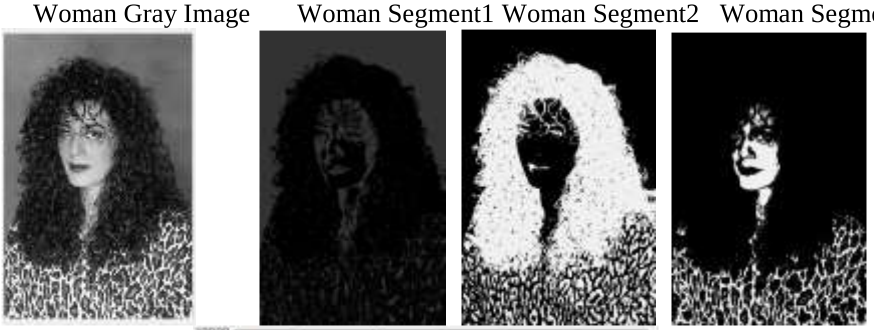


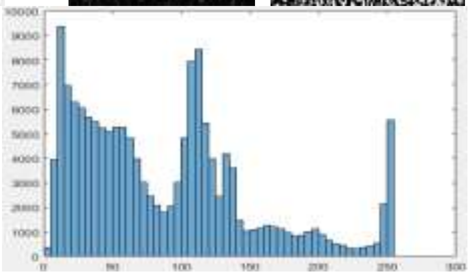
Figure 3. Plots of Eagle Probability Density and TPLTM Estimated by EM

Table5.1c: TPLTM ML Estimates for WOMAN data for (K=3)

Parameters	Estimation of Initial Parameters			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	0.5185	0.3276	0.1539
μ_i	219.6327	115.5619	406.2072	37.9456	113.7363	275.2941
σ_i^2	920.5615	406.2072	5738.391	0.1539	203.4988	1661.1735

Woman Gray Image Woman Segment1 Woman Segment2 Woman Segment3





Woman Histogram

Table5.1d: ML Estimates for OCEAN data for (K=3)

Parameters	Estimation of Initial Parameters			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	0.1125	0.4057	0.4818
μ_i	73.19798	125.4605	189.7868	71.4318	125.1441	190.4335
σ_i^2	287.4086	166.946	135.257	314.8066	250.8708	121.0660

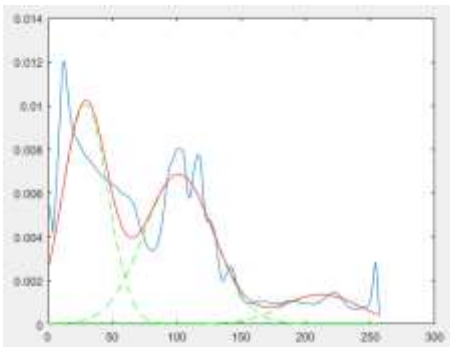
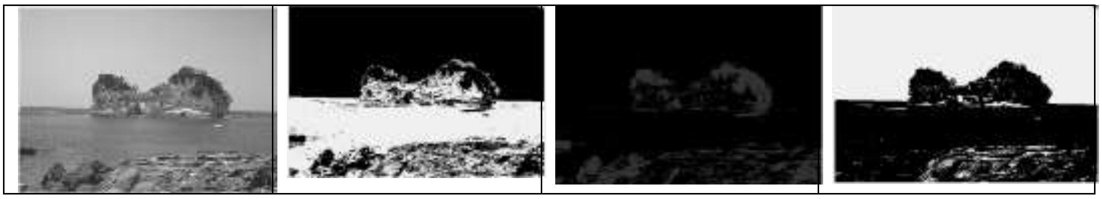
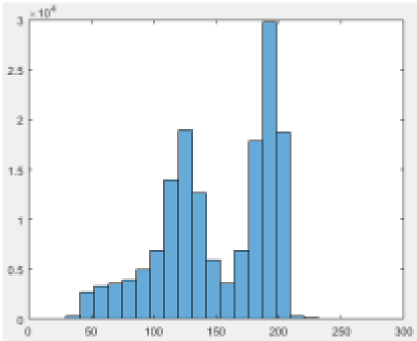


Figure 4. Plots of Woman Probability Density and TPLTM Estimated by EM

Ocean Gray Image Ocean Segment 1 Ocean Segment2 Ocean Segment3





Ocean Histogram

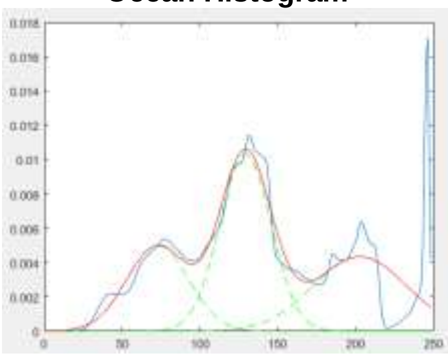
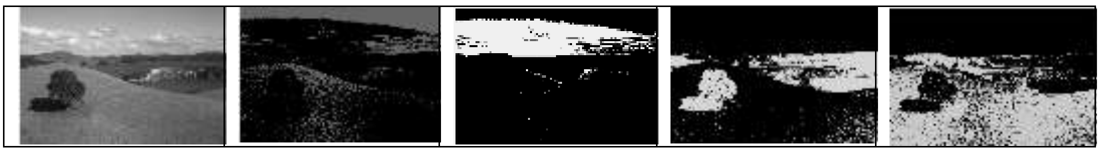


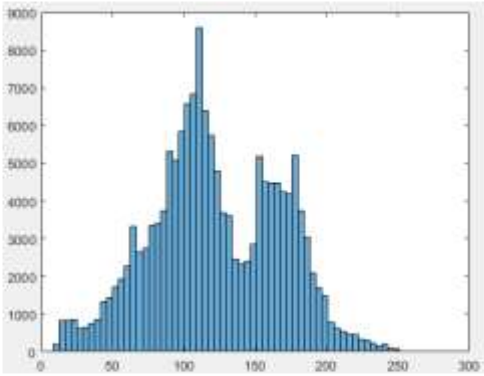
Figure 5. Plots of Ocean Probability Density and TPLTM Estimated by EM

Table5.1e: ML Estimates for Hills data for (K=3)

Parameters	Estimation of Initial Parameters				Estimation of final Parameters by EM Algorithm			
	Image Region				Image Region			
	1	2	3	4	1	2	3	4
α_i	0.25	0.25	0.25	0.25	0.2006	0.4309	0.2577	0.1108
μ_i	189.4223	58.9282	107.5300	154.6640	63.7706	108.2456	165.3506	182.3580
σ_i^2	238.8511	364.34	152.8167	130.2383	591.9581	272.2306	261.4220	709.7667

Hills Grey Image Hills Segment 1 Hills Segment2 Hills Segment3 Hills Segment4





Hills Histogram

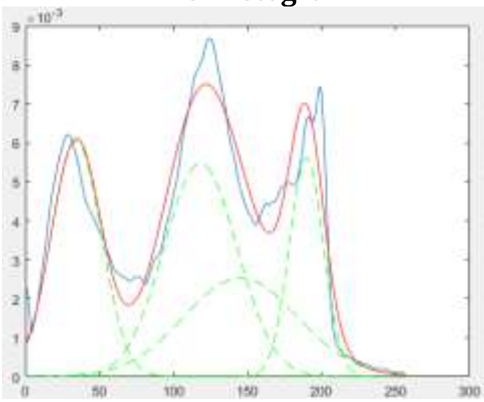


Figure 6. Plots of Hills Probability Density and TPLTM Estimated by EM

Substituting the last gauges of the reproduction restrictions, the likelihood thickness capacity of pixel powers of each picture is assessed.

The Estimated probability density function of pixel intensities of the image OSTRICH

$$f(x_s,\theta^{(i)}=(0.9247)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-74.8295}{26.18200}\right)^2\right]e^{-\left(\frac{x_{(s)}-74.8295}{26.18200}\right)}}{(26.18200)\left[1+e^{-\left(\frac{x_{(s)}-74.8295}{26.18200}\right)^2}\right]}$$

$$+(0.0753)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-161.528}{38.95371}\right)^2\right]e^{-\left(\frac{x_{(s)}-161.528}{38.95371}\right)}}{(38.95371)\left[1+e^{-\left(\frac{x_{(s)}-161.528}{38.95371}\right)^2}\right]}$$

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

$$f(x_s,\theta^{(l)}) = (0.93891)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-113.2905}{11.394797}\right)^2\right]e^{-\left(\frac{x_{(s)}-113.2905}{11.394797}\right)}}{(11.394797)\left[1+e^{-\left(\frac{x_{(s)}-113.2905}{11.394797}\right)^2}\right]} +(0.06109)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-56.1087}{33.81601}\right)^2\right]e^{-\left(\frac{x_{(s)}-56.1087}{33.81601}\right)}}{(33.81601)\left[1+e^{-\left(\frac{x_{(s)}-56.1087}{33.81601}\right)^2}\right]}$$

The Estimated likelihood thickness capacity of pixel forces of the picture OCEAN is,

$$f(x_s,\theta^{(l)}) = (0.1125)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-71.4318}{17.74279}\right)^2\right]e^{-\left(\frac{x_{(s)}-71.4318}{17.74279}\right)}}{(17.74279)\left[1+e^{-\left(\frac{x_{(s)}-71.4318}{17.74279}\right)^2}\right]} +(0.4057)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-125.1441}{15.83890}\right)^2\right]e^{-\left(\frac{x_{(s)}-125.1441}{15.83890}\right)}}{(15.83890)\left[1+e^{-\left(\frac{x_{(s)}-125.1441}{15.83890}\right)^2}\right]} +(0.4818)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-190.4335}{11.002999}\right)^2\right]e^{-\left(\frac{x_{(s)}-190.4335}{11.002999}\right)}}{(11.002999)\left[1+e^{-\left(\frac{x_{(s)}-190.4335}{11.002999}\right)^2}\right]}$$

The Estimated probability density function of pixel intensities of the image WOMAN is

$$f(x_s,\theta^{(l)}) = (0.5185)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-37.9456}{21.34370}\right)^2\right]e^{-\left(\frac{x_{(s)}-37.9456}{21.34370}\right)}}{(21.34370)\left[1+e^{-\left(\frac{x_{(s)}-37.9456}{21.34370}\right)^2}\right]} +(0.3276)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-113.7363}{16.59198}\right)^2\right]e^{-\left(\frac{x_{(s)}-113.7363}{16.59198}\right)}}{(16.59198)\left[1+e^{-\left(\frac{x_{(s)}-113.7363}{16.59198}\right)^2}\right]} +(0.1539)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-203.4988}{40.757496}\right)^2\right]e^{-\left(\frac{x_{(s)}-203.4988}{40.757496}\right)}}{(40.757496)\left[1+e^{-\left(\frac{x_s-203.4988}{40.757496}\right)^2}\right]}$$

The Estimated likelihood thickness capacity of pixel forces of the picture HILLS is,

$$f(x_s,\theta^{(l)}=(0.2006)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-63.7706}{24.33018}\right)^2\right]e^{-\left(\frac{x_{(s)}-63.7706}{24.33018}\right)}}{(24.33018)\left[1+e^{-\left(\frac{x_{(s)}-63.7706}{24.33018}\right)^2}\right]}+$$

$$+(0.4309)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-108.2456}{16.49941}\right)^2\right]e^{-\left(\frac{x_{(s)}-108.2456}{16.49941}\right)}}{(16.49941)\left[1+e^{-\left(\frac{x_{(s)}-108.2456}{16.49941}\right)^2}\right]}+$$

$$+(0.2577)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-165.3506}{16.168549}\right)^2\right]e^{-\left(\frac{x_{(s)}-165.3506}{16.168549}\right)}}{(16.168549)\left[1+e^{-\left(\frac{x_{(s)}-165.3506}{16.168549}\right)^2}\right]}+$$

$$+(0.1108)\frac{\left[\frac{3}{(12+\pi^2)}\right]\left[4+\left(\frac{x_{(s)}-182.3580}{26.64144}\right)^2\right]e^{-\left(\frac{x_{(s)}-182.3580}{26.64144}\right)}}{(26.64144)\left[1+e^{-\left(\frac{x_{(s)}-182.3580}{26.64144}\right)^2}\right]}$$

Utilizing the evaluated likelihood thickness capacity and picture division calculation given in segment 2.1, the picture division is improved the situation the five pictures under thought, the first and divided pictures are appeared in Figure 5.

Original Images **Segmented Images**

Figure 6. Original and Segmented Image

6. Performance Evaluation

In the wake of leading the try different things with the picture division calculation created in this paper, its execution is considered. The execution assessment of the division system is conveyed by acquiring the three execution measures namely, (i) probabilistic rand index(PRI), (ii) variety of information(VOI) and (iii) worldwide consistence error(GCE). The execution of the created calculation utilizing limited two parameter logistic type blend display with k-implies bunching (TPLT MM-K) is examined by registering the division execution measures in particular, PRI, GCE, and VOI for the five pictures under examination. The processed estimations of the execution events for the new and the prior existing limited Gaussian blend demonstrate (GMM) with k-implies calculation are exhibited in Table 6 for a relative report.

Table 6 SEGMENTATION PERFORMANCE MEASURES

IMAGES	METHOD	PERFORMANCE MEASURES		
		PRI	GCE	VOI
OSTRICH	GMM	0.9147	0.2785	0.4273
	TPLTMM-K	0.9180	0.2299	0.1867
WOMAN	GMM	0.8876	0.0232	0.1417
	TPLTMM-K	0.8928	0.0199	0.1479
OCEAN	GMM	0.8852	0.0339	0.1927
	TPLTMM-K	0.8869	0.0266	0.1593
HILLS	GMM	0.8688	0.2572	0.3357
	TPLTMM-K	0.8913	0.1640	0.2607
EAGLE	GMM	0.9987	0.0023	0.0126
	TPLTMM-K	0.9994	0.0016	0.0069

From Table 6, it is watched that the PRI estimations of the projected calculation for the five pictures measured for the testing are more than that of the qualities from the division calculation in light of limited Gaussian blend demonstrate with K-implies. Likewise, GCE and VOI estimations of the proposed calculation are not as much as that of limited Gaussian blends show. This uncovers the proposed calculation beats the current calculation in view of the limited Gaussian blend show.

In the wake of building up the picture division technique it is expected to check the utility of division in show working of the picture for picture recovery. The execution assessment of the recovered picture should be possible by personal picture quality testing or by target picture excellence difficult. The target picture quality testing strategies are regularly utilized since the numerical consequences of a target measure permit a steady examination of various calculations. There are a few picture quality measures accessible for execution assessment of the picture division technique. Utilizing the evaluated likelihood thickness elements of the pictures under thought the recovered pictures are acquired and are appeared in Figure 7.

Original and Retrieved Image

ORIGINAL IMAGES **RETRIVED IMAGES**

Figure 7. The Original and Retrieved Images

OSTRICH, OCEAN, WOMAN, HILLS and EAGLE using the proposed model and finite GMM with K-means and their values are given in the Table 7

IMAGES	Quality Metrics	GMM	TPLTMM	Standard Limits
OSTRICH	Average Difference	0.5315	0.5104	Close to 0
	Maximum Distance	0.4763	0.5273	Close to 1
	Image Fidelity	0.8124	0.8247	Close to 1
	Mean Square Error	0.0770	0.0711	Close to 0
	Signal to Noise Ratio	14.080	14.323	As big as possible
	Image Quality Index	0.8460	0.8580	Close to 1
WOMAN	Average Difference	0.4860	0.5420	Close to 0
	Maximum Distance	0.9435	0.9792	Close to 1
	Image Fidelity	0.4620	0.4801	Close to 1
	Mean Square Error	0.0803	0.0750	Close to 0
	Signal to Noise Ratio	4.7261	4.9811	As big as possible
	Image Quality Index	0.9782	0.9884	Close to 1
OCEAN	Average Difference	0.3211	0.2101	Close to 0
	Maximum Distance	0.6810	0.6541	Close to 1
	Image Fidelity	0.6885	0.6954	Close to 1
	Mean Square Error	0.0645	0.0451	Close to 0
	Signal to Noise Ratio	4.0802	4.2540	As big as possible
	Image Quality Index	0.7763	0.8514	Close to 1
HILLS	Average Difference	0.2664	0.1198	Close to 0
	Maximum Distance	0.7664	0.8198	Close to 1
	Image Fidelity	0.9348	0.9846	Close to 1
	Mean Square Error	0.0138	0.0132	Close to 0
	Signal to Noise Ratio	0.9383	0.9404	As big as possible
	Image Quality Index	0.5710	0.6250	Close to 1
EAGLE	Average Difference	0.2350	0.4581	Close to 0
	Maximum Distance	0.5925	0.6547	Close to 1
	Image Fidelity	0.9882	0.9981	Close to 1
	Mean Square Error	0.0038	0.0012	Close to 0
	Signal to Noise Ratio	11.1494	14.521	As big as possible
	Image Quality Index	0.9869	0.9914	Close to 1

From Table 7, it is watched that all the picture superiority procedures for the five pictures are gathering the normal criterion. This suggests utilizing the projected calculation the pictures are recovered precisely.

8. Conclusion

This paper deals with a novel application of two parameters logistic type distribution in image segmentation. The two parameter logistic type distribution includes a family of platykurtic distributions. The modernized equations of the current method with various parameters are derived and solved using matlab code. Experimentation with five images taken from Berkeley-image database revealed that the proposed algorithm achieves better with respect to picture segmentation metric that image segmentation metrics method of GMM. The hybridization of replica base advance method with k-means improves the efficiency of segmentation. The projected algorithm can be further extended to the other method of estimation of the model parameters such as Monto-Carlo methods and Bootstrapping methods which will be taken elsewhere.

References

[1] Srinivas. Y and Srinivas Rao. K (2007), "Unsupervised image segmentation using finite doubly truncated Gaussian mixture model and Hierarchial clustering", Journal of Current Science, Vol.93, No.4, pp.507-514.

[2] T. Yamazaki (1998) "Introduction of algorithm into color image segmentation," Proceedings of ICIRS'98, pp. 368–371.

[3] T. Jyothirmayi, et al(2016)., "Image Segmentation Based on Doubly Truncated Generalized Laplace Mixture Model and K Means Clustering International Journal of Electrical and Computer Engineering (IJECE), Vol. 6, No. 5, October 2016, pp. 2188~2196.

[4] T. Jyothirmayi, et al (2017)., "Performance Evaluation of Image Segmentation Method based on Doubly Truncated Generalized Laplace Mixture Model and Hierarchical Clustering" **.** J. Image, Graphics and Signal Processing, 2017, 1, 41-49.

[5] The Berkeley segmentation dataset http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/BSDS300/html/dataset/images.html**.**

[6] 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.

[7] Karim Kalti, et al., "Image Segmentation by Gaussian Mixture Models and Modified FCM Algorithm", "The International Arab Journal of Information Technology", Vol. 11, No. 1, January 2014.

[8] M.Seshashayee, K. Srinivasa rao, Ch.Satyanarayana and P.Srinivasa rao- (2011) – Studies on Image Segmentation method Based on a New Symmetric Mixture Model with K – Means, Global journal of Computer Science and Technology, Vol.11, No.18, pp.51-58. ISSN: 0975-4172, 0975-4350.

[9] GVS.Rajkumar, K. Srinivasa rao, and P.Srinivasa rao-(2011) – Studies on color Image segmentation technique based on finite left truncated Bivariate Gaussian mixture model with k - means, Global Journal of computer Science and Technology, Vol.11, No.18, pp 21- 30. ISSN: 0975-4172, 0975-4350.

[10] GVS.Rajkumar K.Srinivas rao**,** P.Srinivasa rao (2011) – studies on color image segmentation technique based on finite left truncated bivariate gaussian mixture model with k-means, global journal of computer science and technology, vol.11, no.18. Issn: 0975-4172, 0975-4350.