IMAGE SEGMENTATION METHOD BASED ON LOGISTIC DISTRIBUTION WITH K-MEANS CLUSTERING

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ABSTRACT- This paper deals with the utilization of logistic distribution in image segmentation. The proposed algorithm is having application in medical diagnostics, security and surveillance analysis, etc. This algorithm serves as a generalization of the image segmentation with Gaussian mixture models since the logistic 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 logistic distribution. The model parameters are estimated using EM-algorithm. The initialization of parameters is done with k-means algorithm and moment method of estimation. The performance of the developed algorithm is studied through conducting an experimentation with five images randomly taken from Berkeley-image database and using the segmentation metrics PRI, GCE ,VOI. It is observed that this algorithm outperform the existing algorithm in segmenting for the images, which have platy kurtic distribution of pixel intensities.

Keywords:- Image segmentation , logistic distribution, EM-algorithm, performance evaluation.

I. INTRODUCTION

For image processing and analysis of image segmentation is a prime consideration. In segmentation we separate the objects of interest in the image, which characterize the process of dividing the image into homogenous image regions. Image segmentation can be done based on regions ,edges, thresh hold and models[1]-[4].Among these methods model based image segmentation is more efficient compared to the other methods (Srinivasa Rao K and Y srinivas(2007)). In the model based segmentation method the whole image is characterized by a mixture of probability distributions. The pixel intensity is considered as a feature for image segmentation. The pixel intensities in an image region may be distributed as platykurtic and laptokurtic, and mesokurtic. Due to simplicity and computational convenience, image segmentation algorithms based on Gaussian mixture models were developed (Yamazaki et al,(1998),T.Lie et al(1993), N.Nasios et al(2006),Z.H.Zhang et al (2003)). However in Gaussian mixture models the pixel intensities in image region are meso kurtic. But in many image regions the pixel intensities may not be distributed as mesokurtic, even though they are symmetric. Hence, to have a close approximation to the pixel densities, it is needed to consider an alternative to the Gaussian distribution which is symmetric. Seshashayee et al (2011),Jyothirmayi et al (2016),(2017), Srinivara Rao et al (2011), have developed some image segmentation methods based on New Symmetric Mixture models, and mixture of generalized Laplace models. Recently Srinivara Rao et al(2018) have introduced a logistic type distribution which is very useful in portraying symmetric and platykurtic distributions. No work has been reported in literature regarding the use of logistic distribution in image segmentation. In this paper we develop and analyze the image segmentation algorithm using mixture of logistic distribution.

The rest of the paper is organized as follows: in section-2, the mixture of two parameter logistic type distribution and its properties are discussed ,in section-3 the estimation of the model parameters using EM-algorithm is studied,in section-4,initialization of the model parameters using k-means algorithm and moment method of estimation 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 proposed algorithm is studied by experimentation with five images randomly taken from Berkeley image database and computing the performance measure such as PRI,GCE,VOI.In section-7 a comparative study of developed algorithm with that of existing algorithms is presented. Section-8 deals with conclusions.

II. LOGISTIC DISTRIBUTION

In this section, we briefly present the logistic distribution. In each image region the image data is quantified by pixel intensities. To model the pixel intensities of the image region it is assumed that the pixel intensities of the image region follow a logistic distribution given by Srinivasa Rao K, et al.,(2018).

The probability density function of the pixel intensity is given by

$$f\left(x,\mu,\sigma^2\right)=\frac{e^{\frac{-(x-\mu)}{\sigma^2}}}{\sigma^2\left(1+e^{\frac{-(x-\mu)}{\sigma^2}}\right)^2},-\infty<x<\infty,-\infty<\mu<\infty,\sigma>0$$

The frequency curve associated with logistic distribution is shown in figure.

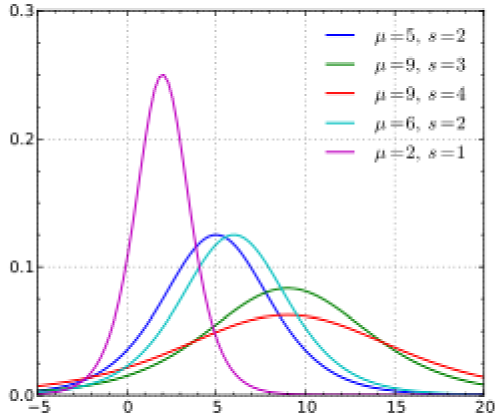


Figure : Frequency curve of logistic Distribution

The distribution is symmetric about μ and the distribution function

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

The entire image is a collection of regions which are characterized by logistic distribution . Hence, it is assumed that the pixel intensities of the whole image follows k-component mixture of two parameter logistic type distribution and its probability density function is of the form.

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

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 ith region in the whole image.

In general the pixel intensities in the regions are statically correlated and these correlations can be reduced by spatial sampling (Lei 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

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

III. ESTIMATION OF MODEL PARAMETERS USING EM ALGORITHM:-

The parameters of the model are estimated by using likelihood function of the sample observations. The likelihood equations are usually found by differentiating the logarithm of likelihood function, setting the derivatives equal to zero, and perhaps performing some additional algebraic manipulations. 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 updated equations of the model parameters are obtained for Expectation Maximization (EM) algorithm.

The likelihood of the function of model, is

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

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

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

Therefore

$$\log L(\theta) = \sum_{S=1}^{N} \log \left[\sum_{i=1}^{k} \alpha_i \frac{e^{\frac{-(x-\mu)}{\sigma^2}}}{\sigma^2 \left(1 + e^{\frac{-(x-\mu)}{\sigma^2}}\right)^2} \right] \tag{5}$$

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

E-STEP:-

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

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

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

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

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

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

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

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

The expectation of the log likelihood function of the sample is

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

But we have

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

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 obtaining the estimation of model parameters one has to maximize $Q(\theta, \theta^{(l)})$ 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

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

Where, λ is Lagrangian multiplier combining the constraint with the log likelihood functions to be maximized.

The above two steps are repeated as necessary, each iteration is guaranteed to increase the loglikehood and the algorithm is guaranteed to converge to a local maximum of the likelihood function

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

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

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

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

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

$$\frac{\partial}{\partial \mu_i}\left[\sum_{s=1}^{N}\sum_{i=1}^{K} P_i(x_{s.},\theta^l)\log \alpha_i \frac{e^{\left[\frac{-(x_s-\mu_i^{(l)})}{\sigma^{(l)}}\right]}}{\sigma^{2(l)}\left(1+e^{\left[\frac{x_s-\mu_i^{(l)}}{\sigma^{(l)}}\right]}\right)^2}\right]=0 \qquad (17)$$

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

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

This implies

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

After Simplifying, we get

We get $$\mu_i=\frac{\sum_{s=1}^{N}\left[\left[\frac{x_s}{\left((x_s-\mu_i)^2\right)}\right]-\left[\frac{1}{\sigma_i}\right]+\left[\frac{2}{\sigma_i\left(1+e^{\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right]p_i(x_s,\theta^l)}{\sum_{s=1}^{N}\frac{p_i(x_s,\theta^l)}{\left((x_s-\mu_i)^2\right)}} \qquad (20)$$

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

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

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

Taking the partial derivative with respect to σ_i^2

$$\frac{\partial}{\partial\sigma_i^2}\left[\sum_{s=1}^{N}\sum_{i=1}^{K}P_i(x_{s.},\theta^l)\log\alpha_i\frac{e^{\frac{-(x-\mu)}{\sigma^2}}}{\sigma^2\left(1+e^{\frac{-(x-\mu)}{\sigma^2}}\right)^2}\right]=0 \qquad (24)$$

The above equation yields

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

Simplifying the above equation we have

This implies,

$$\sum_{s=1}^{N}p_i(x_s,\theta^{(l)})\left[\left[\frac{-(x_s-\mu_i)^2\sigma_i^2}{\sigma_i^4(4\sigma_i^2+(x_s-\mu_i)^2}\right]+\left[\frac{(x_s-\mu_i)}{\sigma_i^3}\right]-\left[\frac{1}{2\sigma_i^2}\right]-\left[\frac{(x_s-\mu_i)^2}{\sigma_i^4\left(1+e^{\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right]=0 \qquad (24)$$

After simplification the above equation can written as

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

$$\sigma_i^{2^{(l+1)}} = \frac{\sum_{s=1}^{N}\left[\left[\frac{(x_s-\mu_i^{(l+1)})}{\sigma_i^{3^{(l)}}}\right]-\left[\frac{(x_s-\mu_i^{(l+1)})^2}{\sigma_i^{4}\left(1+e^{\left(\frac{x_s-\mu_i^{(l+1)}}{\sigma_i^{(l)}}\right)^2}\right)}\right]\right]p_i(x_s,\theta^{(l)})}{\sum_{s=1}^{N}\frac{(x_s-\mu_i^{(l+l)})\,p_i(x_s,\theta^{(l)})}{\sigma_i^{3^{(l)}}((x_s-\mu_i^{(l+1)})^2)}} \qquad (25)$$

Where,

$$p_i(x_s,\theta^{(l)}) = \left[\frac{\alpha_i^{(l+1)} f_i(x_s,\mu_i^{(l+1)},\sigma_i^{2^{(l)}})}{\sum_{i=1}^{k}\alpha_i^{(l+1)} f_i(x_s,\mu_i^{(l+1)},\sigma_i^{(l)})}\right] \qquad (26)$$

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 taken for k-means algorithm is obtained, by plotting the histogram of the pixel intensities of the whole image, and the number of peaks in the histogram can be taken as the initial value of the number of regions k.

The parameters α_i , μ and σ^2 are usually considered as known apriori. A commonly used method in initializing parameters is by drawing a random sample from the entire image (McLachan G. AND Peel D.(2000). This method performs well, if 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 homogeneous regions. In k-means algorithm the centroids of the clusters are recomputed as soon as the pixel joins a cluster.

The k-means algorithm is one of the clustering techniques for which the objective is to find the partition of the data which minimizes the squared distances between all points and their respective cluster centers (Rose H.Turi,(2001)).

k-means algorithm uses an iterative procedure that minimizes the sum 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 dataset as initial clusters. These data points represent initial cluster centroids.
2. Calculate Euclidian distance of each data point from each cluster centre and assign the data points to its nearest cluster center.
3. Calculate new cluster center 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 the cluster centers are only updated once all points have been allocated to their closed cluster center. k-means algorithm depends on the parameter k, the number of clusters in the image.

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 K, et.al., (1997) for two parameter logistic distribution .

The initial estimate as $\alpha_i = \frac{1}{k}$, where i=1,2,3………………k. The parameter μ_i and σ_i^2 are estimated by the method of moments 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.

4.2 SEGMENTATION ALGORITHEM

In this section, we present the image segmentation algorithm. After refining the parameters, the prime step in image segmentation on 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 estimates for each image region as discussed in section 1.4.

Step 3) Obtain the refined estimates of the model parameters μ_i, σ_i^2 and α_i for i=1,2,3……k, Using the EM algorithm with the updated equations given by (5),(7),And (8) respectively in section 3.3.

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

$$L_j = MAX\left[\frac{e^{\frac{-(x-\mu)}{\sigma^2}}}{\sigma^2\left(1+e^{\frac{-(x-\mu)}{\sigma^2}}\right)^2}\right], -\infty < x_s < \infty, -\infty < \mu_j < \infty, \sigma_j > 0$$

V. EXPERIMENTATION AND RESULTS

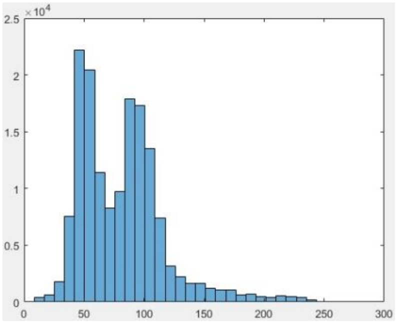
The EM algorithm for model has been implemented in MATLAB and tested its efficiency for image segmentation. To demonstrate the utility of the image segmentation algorithm developed, an experiment is conducted with five images taken from Berkeley

Images data.The images AIR CRAFT,TREE,DEAR,STAR FISH, and TIGER are considered for image segmentation. The pixel intensities of the image are assumed to follow a logistic distribution. We consider that the image contains k regions and pixel intensities in each image region follow a logistic distribution with different parameters. The number of segments in each of 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 1.2 Air Craft ,Tree,Dear,Star Fish, And Tiger

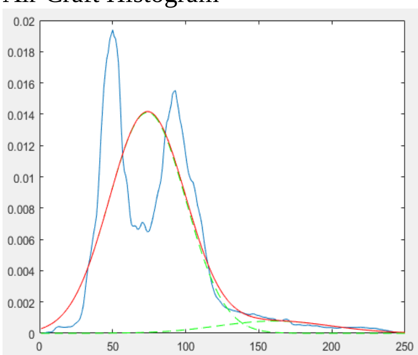
Table 5.1a: ML Estimates for Ostrich data for(K=2)

Air Craft Grey image

Air Craft Segment

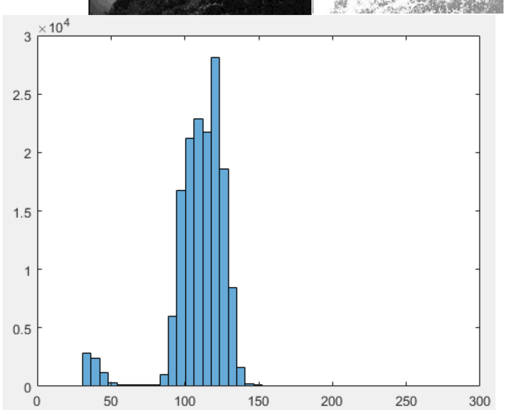


Air Craft Histogram

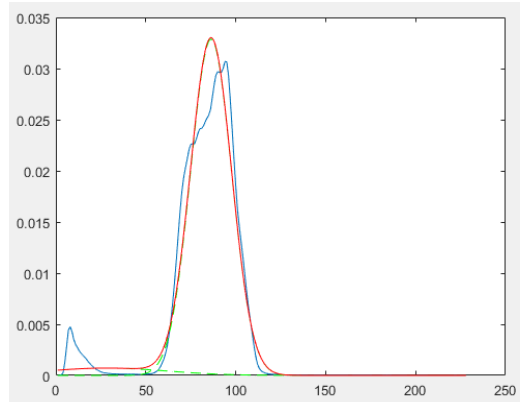


Plots of Air Craft **Probability Density and logistic Estimated by EM**

TREE GREY IMAGE TREE SEGMENTEDIMAGE



Tree Histogram

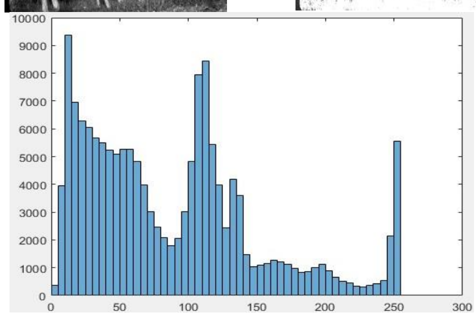


Plots of Tree **Probability Density logistic Estimated by EM**

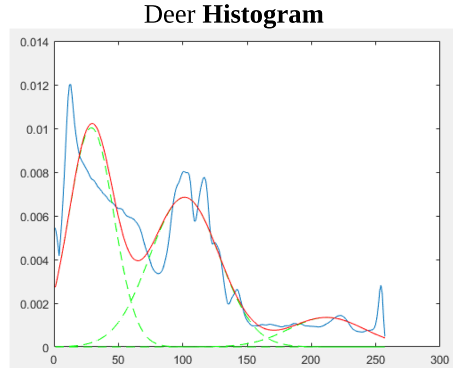
Table: logistic ML Estimates for WOMAN data for (K=3)

Deer Gray Image

Deer Segment



Deer **Histogram**

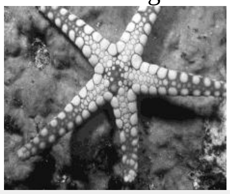


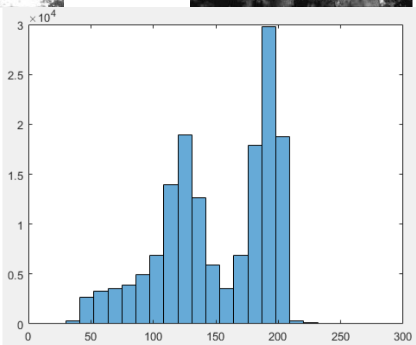
Plots of Deer **Probability Density logistic Estimated by EM**

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

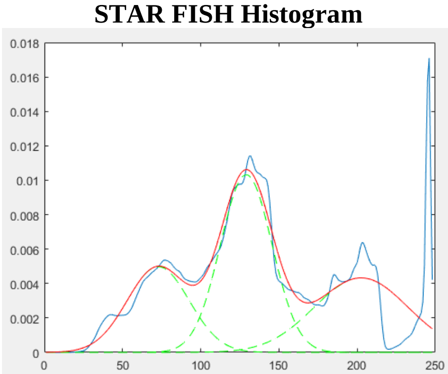
Star Fish Gray Image

Star Fish Segment





STAR FISH Histogram

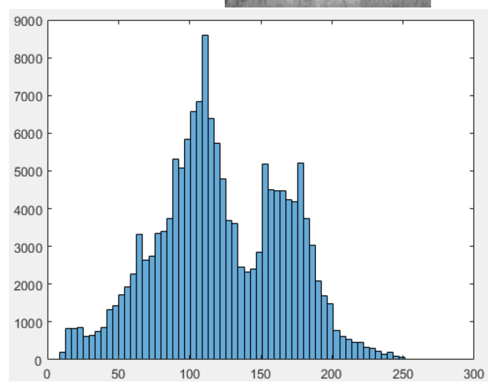


Plots of STAR FISH Probability Density logistic Estimated by EM

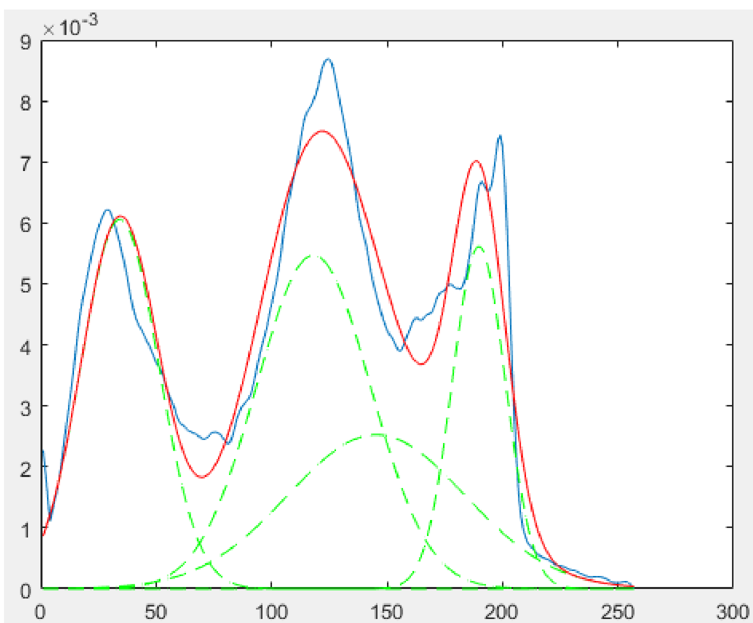
Table5.1e: ML Estimates for Tiger data for (K=3)

Tiger Grey Image

Tiger Segment



Tiger Histogram



Plots of Tiger Probability Density of logistic Estimated by EM

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 pixel intensities of the image Air Craft

$$f(x_s,\theta^{(l)} = (0.8247)\frac{\left[\left(\frac{x_{(s)}-54.8295}{26.18200}\right)^2\right]e^{-\left(\frac{x_{(s)}-14.8295}{26.18200}\right)}}{(16.18200)\left[1+e^{-\left(\frac{x_{(s)}-14.8295}{26.18200}\right)^2}\right]} + (0.0753)\frac{\left[\left(\frac{x_{(s)}-161.528}{38.95371}\right)^2\right]e^{-\left(\frac{x_{(s)}-161.528}{38.95371}\right)}}{(38.95371)\left[1+e^{-\left(\frac{x_{(s)}-161.528}{38.95371}\right)^2}\right]}$$

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

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

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

$$f(x_s,\theta^{(l)} = (0.1125)\frac{\left[\left(\frac{x_{(s)}-51.4318}{17.74279}\right)^2\right]e^{-\left(\frac{x_{(s)}-71.4318}{17.74279}\right)}}{(16.74279)\left[1+e^{-\left(\frac{x_{(s)}-71.4318}{17.74279}\right)^2}\right]} + (0.4457)\frac{\left[\left(\frac{x_{(s)}-145.1441}{16.83890}\right)^2\right]e^{-\left(\frac{x_{(s)}-125.1441}{15.83890}\right)}}{(16.83890)\left[1+e^{-\left(\frac{x_{(s)}-145.1441}{15.83890}\right)^2}\right]}$$

The Estimated probability density function of pixel intensities of the image Star Fish is

$$f(x_s,\theta^{(l)} = (0.5185)\frac{\left[\left(\frac{x_{(s)}-37.9456}{21.34370}\right)^2\right]e^{-\left(\frac{x_{(s)}-37.9456}{21.34370}\right)}}{(21.34370)\left[1+e^{-\left(\frac{x_{(s)}-37.9456}{21.34370}\right)^2}\right]}$$

$$+(0.3276)\frac{\left[\left(\frac{x_{(s)}-113.7363}{16.59198}\right)^2\right]e^{-\left(\frac{x_{(s)}-113.7363}{16.59198}\right)}}{(16.59198)\left[1+e^{-\left(\frac{x_{(s)}-113.7363}{16.59198}\right)^2}\right]}+(0.1539)\frac{\left[\left(\frac{x_{(s)}-203.4988}{40.757496}\right)^2\right]e^{-\left(\frac{x_{(s)}-203.4988}{40.757496}\right)}}{(40.757496)\left[1+e^{-\left(\frac{x_s-203.4988}{40.757496}\right)^2}\right]}$$

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

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

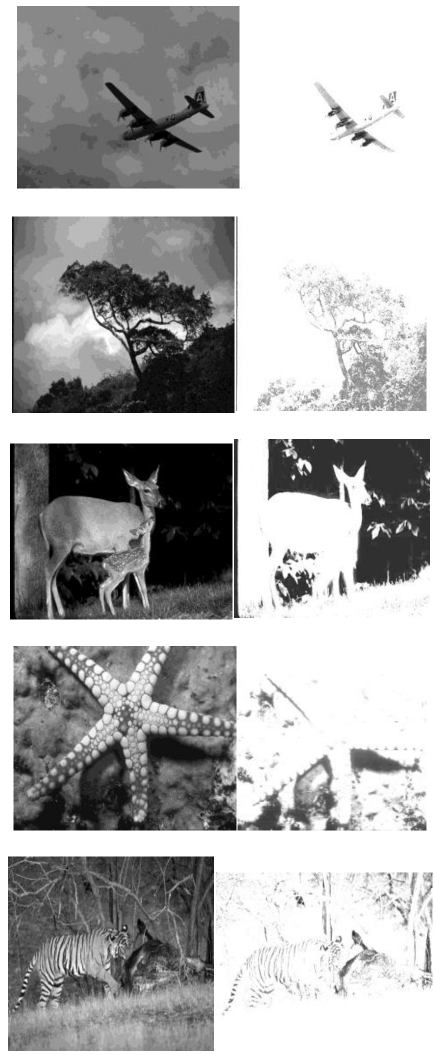
$$+(0.4309)\frac{\left[\left(\frac{x_{(s)}-108.2456}{16.49941}\right)^2\right]e^{-\left(\frac{x_{(s)}-108.2456}{16.49941}\right)}}{(16.49941)\left[1+e^{-\left(\frac{x_{(s)}-108.2456}{16.49941}\right)^2}\right]}+(0.2577)\frac{\left[\left(\frac{x_{(s)}-165.3506}{16.168549}\right)^2\right]e^{-\left(\frac{x_{(s)}-165.3506}{16.168549}\right)}}{(16.168549)\left[1+e^{-\left(\frac{x_{(s)}-165.3506}{16.168549}\right)^2}\right]}$$

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

Using the estimated probability density function and image segmentation algorithm given in section 2.1, the image segmentation is done for the five images under consideration, The original and segmented images are shown in Figure 5.2

5.2 Original and Segmented Image

ORIGINAL IMAGES SEGMENTEDIMAGES



VI. PERFORMANCE EVALUATION

After conducting the experiment with the image segmentation algorithm developed in this paper, 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 computed values of the performance measures for the new and the earlier existing finite Gaussian mixture model (GMM) with k-means algorithm are presented in the Table for a comparative study. From the Table 6.3, 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.

VII. COMPARATIVE STUDY

A comparative study of the proposed algorithm with that of the algorithms based on finite Gaussian mixture model reveals that the MSE of the proposed model is less than that of finite Gaussian mixture model. Based on all other quality metrics.it is also observed that the performance of the proposed model in retrieving the images is better than the Gaussian mixture model.

IMAGES	Quality Metrics	GMM	logistic	Standard Limits
AIRCRAFT	Average Difference	0.3315	0.3104	Close to 0
	Maximum Distance	0.3763	0.4273	Close to 1
	Image Fidelity	0.7124	0.9247	Close to 1
	Mean Square Error	0.0770	0.3711	Close to 0
	Signal to Noise Ratio	10.080	14.323	As big as possible
	Image Quality Index	0.9460	0.9580	Close to 1
TREE	Average Difference	0.5860	0.4420	Close to 0
	Maximum Distance	0.2435	0.5792	Close to 1
	Image Fidelity	0.3620	0.8801	Close to 1
	Mean Square Error	0.0803	0.0750	Close to 0
	Signal to Noise Ratio	4.8261	4.9811	As big as possible
	Image Quality Index	0.2782	0.9884	Close to 1
DEER	Average Difference	0.3211	0.2101	Close to 0
	Maximum Distance	0.7810	0.6541	Close to 1
	Image Fidelity	0.7885	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	0.9763	0.8514	Close to 1
STARFISH	Average Difference	0.3664	0.1198	Close to 0
	Maximum Distance	0.4664	0.8398	Close to 1
	Image Fidelity	0.9348	0.9446	Close to 1
	Mean Square Error	0.0138	0.0432	Close to 0
	Signal to Noise Ratio	0.9383	0.9404	As big as possible
	Image Quality Index	0.4710	0.6450	Close to 1
TIGER	Average Difference	0.2350	0.4581	Close to 0
	Maximum Distance	0.3925	0.3347	Close to 1
	Image Fidelity	0.4882	0.3381	Close to 1
	Mean Square Error	0.2038	0.0412	Close to 0
	Signal to Noise Ratio	10.1494	14.421	As big as possible
	Image Quality Index	0.4869	0.8914	Close to 1

VIII. CONCLUSION

This paper deals with a novel application of logistic distribution in image segmentation. The whole image is characterized by a finite mixture of logistic distribution. The logistic distribution includes a family of platykurtic distributions. The updated equations of the model parameters are derived and solved using mat-lab code. The initialization of parameters is done through k-means algorithm and moment method of estimation .An experimentation with five images taken from Berkeley-image database revealed that the proposed algorithm performs better with respect to image segmentation metric that image segmentation metrics method of GMM. The hybridization of model based approach with k-means improves the efficiency of segmentation .The proposed 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.

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