IMAGE SEGMENTATION METHOD BASED ON LOGISTIC DISTRIBUTION WITH HIERARCHICALCLUSTERING ALGORITHM

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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. In literature the image segmentation based on probabilistic models has been studied by several people. In general it is customary that the image segmentation is carried using Gaussian mixture models. But in some images the feature vector of image regions may not be measo kurtic and hence Gaussian mixture models may not suit well. Hence in this paper an image is developed and analyzed for image segmentation using finite mixture of logistic distribution and hierarchal clustering. The EM algorithm is utilized for obtaining the estimation of the model parameters. The model parameters are initialized with moment method of estimation and hierarchal clustering .The component maximum likely hood methods using Bayes principle segmentation is developed. The proposed algorithm performance is examined by computing image segmentation performance measures with an experimentation carried by choosing randomly five images from Berkeley data set. The performance measures revealed that this algorithm segment well the image regions than the existing segmentation methods for some images. 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 ,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 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 logistic distribution.

II. LOGISTIC DISTRIBUTION

In this section, we briefly present the logistic distribution. In each image region the image data is quantified by pixel intensities**.** This section deals with the methodology for obtaining estimates of the parameters involved in the model through Expectation and Maximization algorithm (Mclanchlan G and Krishnan T (1997)). The image region pixel intensities are considered as features of the image. Here the logistic distribution is assumed for modeling the image region pixel intensities. As a result of it the whole image can be characterized with a logistic mixture model. The probability density function (p.d.f) of the pixel intensities as of the form

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.

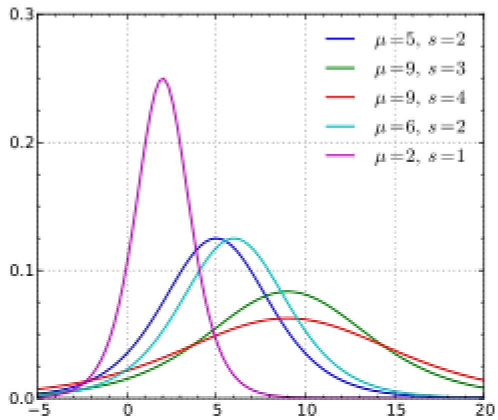


Figure : Frequency curve of logistic Distribution

The 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 $0\le\alpha_i\le 1$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.

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

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

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

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

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

The expectation of the log likelihood function of the sample is

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

But we have

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

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

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

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

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

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

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

Since μ_i appears in only one region, i=1,2,3…………k (regions),
After Simplifying, we get

We get $$\mu_i=\frac{\sum_{s=1}^{N}\left[\left[\frac{x_s}{\left((x_s-\mu_i)^2\right)}\right]-\left[\frac{1}{\sigma_i}\right]+\left[\frac{2}{\sigma_i\left(1+e^{\left(\frac{x_s-\mu_i}{\sigma_i}\right)^2}\right)}\right]\right]p_i(x_s,\theta^l)}{\sum_{s=1}^{N}\frac{p_i(x_s,\theta^l)}{\left((x_s-\mu_i)^2\right)}}$$ Therefore the updated equations of μ_i at $(l+1)^{th}$ iteration is

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

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 $\sigma_i^{\,2}$

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

This implies

Simplifying the above equation we have

This implies,

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

After simplification the above equation can written as

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

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

Where,

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

IV. INITIALIZATION OF THE PARAMETERS BY HIERARCHICAL CLUSTERING

The efficiency of the Expectation and Maximization algorithm is heavily depended on initialization of the parameters the initial value of the weighted parameter α_i can be obtained as $\alpha_i = \frac{1}{K}$, where K is the number of image regions. The hierarchal clustering algorithm can be utilized for dividing the pixel intensities of the whole image into K-groups, each representing image region for each group. The moment method of estimation is adopted obtaining the initial values of the model parameters $\mu_i (i = 1...k)$ and $\sigma_i^2 (i = 1...k)$ the moment estimates of the model parameters are

SEGMENTATION ALGORITHEM:

The image segmentation algorithm is proposed in this section. The model parameters are estimated as discussed in section 2 and 3.To segment we allocate the pixels to the respective image regions. The major steps in image segmentation are as follows:

Step 1:- Hierarchal clustering algorithm is utilized for dividing pixel intensities of the whole image into K-image regions. where K is number of image regions.

Step 2:-compute the initial estimates for the parameters of the model using moment method of estimation for each image region as discussed in section-3.

Step3:- The Expectation and Maximization algorithm with the updated equations of parameters given in section-2 is to be utilized for computing the final parameters of model for K-image regions.

Step-4:-The allocation of each pixel in the whole image into its corresponding j^{th} image region by computing the component maximum likelihood of the each image region as follows. i.e.,

x_s is assigned to the j^{th}region for which L_j is maximum. Where ,Stop the process.

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 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.

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. EXPERMENTAL RESULTS

This section deals with the experimentation of the suggested image segmentation algorithm.The experiment is carried with five randomly taken images namely ,Air Craft, Tree, Deer,Star Fish and Tiger from Berkeley image data base (http://www.eees.berkeley.edu/Research/Projects/CS/Vision/bsds/BSDS300/html). The feature of the images are obtained by considering pixel intensities. The pixel intensities are obtaining by using MATLAB. Assuming that pixel intensities of image regions follows a mixture of two parameter logistic type distribution, the model characterizing the whole image is developed. With the help of hierarchal clustering algorithm, the number of image regions 'K' for each image is obtained as follows

Table 5.1: Refined value of K (Hierarchical Clustering Algorithm)

IMAGE	AIRCRAFT	TREE	DEER	STARFISH	TIGER
Estimate of K	2	3	3	4	2

With the pixel intensities of each image region of each image the starting values for the model parameters μ_i, σ_i^2 and $\alpha_i \geq$ where i=1, 2, 3……K are computed and presented in the Tables 5.2.a, 5.2.b, 5.2.c, 5.2.d, and 5.2.e for different images. With these initial values of the parameters and the Expectation and Maximization algorithm, the refined estimates of parameters are obtained and shown in Tables:

Table: 5.2 Estimates of the parameters for AIRCRAFT Image

Parameters	Initial values of the Parameters		Refined Estimates	
	Image Region		Image Region	
	1	2	1	2
α_i	0.500	0.500	0.2588	0.7412
μ_i	50.54	131.98	79.256	113.25
σ_i^2	96.2568	138.784	385.25	1011.26

AIRCRAFT GREY IMAGE AIRCRAFT SEGMENT

Table:5.3 Estimates of the parameters for TREE Image

Parameters	Initial values of the Parameters			Refined Estimates		
	Image Region			Image Region		
	1	2	3	1	2	3
α_i	0.333	0.333	0.333	0.1468	0.3278	0.5154
μ_i	331.4625	98.546	582.458	49.256	138.254	267.56
σ_i^2	620.5812	412.458	1565.1	599.57	185.25	1678.25

TREE GREY IMAGE TREE SEGMENT

Table:5.4 Estimate of the parameters for DEER Image

Parameters	Initial values of the Parameters			Refined Estimates		
	Image Region			Image Region		
	1	2	3	1	2	3
α_i	0.333	0.333	0.333	0.1866	0.5710	0.2424
μ_i	94.25	145.28	405.28	35.425	365.45	311.89
σ_i^2	358.45	287.85	348.47	458.25	428.25	344.14

DEER GRAY IMAGE DEER SEGMENT

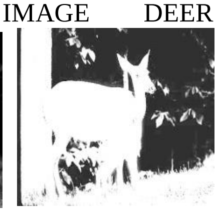
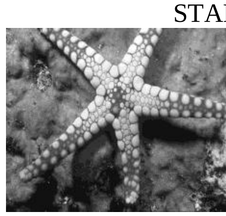


Table:5.5 Estimates of the parameters for STARFISH Image

Parameters	Initial values of the Parameters				Refined Estimates			
	Image Region				Image Region			
	1	2	3	4	1	2	3	4
α_i	0.25	0.25	0.25	0.25	0.3371	0.1374	0.2358	0.2897
μ_i	77.258	174.427	458.44	171.254	83.478	118.41	254.74	154.24
σ_i^2	245.48	364.78	428.57	157.58	941.58	287.42	414.18	641.78

STARFISH GRAY IMAGE STARFISH SEGMENT



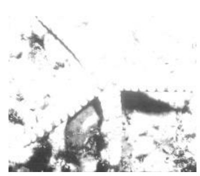


Table:5.6 ML Estimates for TIGER data for (K=2)

Parameters	Initial values of the Parameters		Refined Estimates	
	Image Region		Image Region	
	1	2	1	2
α_i	0.500	0.500	0.0635	0.9365
μ_i	61258	217.45	328.25	45.258
σ_i^2	88.49	284.24	358.25	1045.27

TIGER GRAY IMAGE TIGER SEGMENT

Parameters	Initial values of the Parameters				Refined Estimates			
	Image Region				Image Region			
	1	2	3	4	1	2	3	4
α_i	0.25	0.25	0.25	0.25	0.3371	0.1374	0.2358	0.2897
μ_i	76.258	184.427	358.44	271.254	93.478	218.41	354.74	254.24
σ_i^2	335.48	264.78	228.57	257.58	841.58	387.42	214.18	541.78

VI. COMPARITIVE STUDY OF THE ALGORITHM

This section deals with the performance of the algorithm proposed for image segmentation. The image segmentation quality metrics such as probabilistic rand index (PRI),global consistency error(GCE), variation of information(VOI) are utilized. The Table provides the comparative image segmentation metrics obtained for the five images under experimentation with respective for the proposed algorithm and that of algorithm with GMM reveals that the proposed segmentation algorithm is much superior to that of segmentation algorithm with GMM with respect to the image segmentation quality metrics GCE, PRI and VOI. For the images AIRCRAFT, TREE, DEER, STARFISH and TIGER. Further the efficiency of the proposed segmentation algorithm is also studied by obtaining image quality metrics such as Average Difference, Maximum Distance, Image Fidelity, Mean Square Error, Signal to Noise Ratio, Image Quality Index. Table 6.2 presents the image quality metrics for the five images with respect to the proposed algorithm and the segmentation algorithm with GMM.

The Table 6.2 provides evidences for superiority of image segmentation algorithm with mixture of logistic probability distribution and hierarchal clustering than the other two algorithms under study. The quality metrics of proposed algorithm for the experimental images are very close to the standard values of the metrics.

Also Table 6.2 presents the quality metrics of image segmentation with logistic mixture model and hierarchical clustering algorithm.

Table 6.2 Comparative Study of Image Quality Metrics

IMAGES	Quality Metrics	GMM	logistic-K	logistic-H
AIRCRAFT	Average Difference	0.4315	0.6104	0.5985
	Maximum Distance	0.4763	0.3273	0.5814
	Image Fidelity	0.9124	0.9247	0.8948
	Mean Square Error	0.0770	0.0711	0.0595
	Signal to Noise Ratio	24.080	24.323	11.254
	Image Quality Index	0.3460	0.4580	0.4911
TREE	Average Difference	0.5860	0.6420	0.6948
	Maximum Distance	0.4435	0.8792	0.8784
	Image Fidelity	0.6620	0.5801	0.5915
	Mean Square Error	0.6803	0.1750	0.1645
	Signal to Noise Ratio	4.4261	4.8811	5.8487
	Image Quality Index	0.8782	0.9884	0.8912
DEER	Average Difference	0.4211	0.4101	0.2947
	Maximum Distance	0.7810	0.7541	0.7511
	Image Fidelity	0.8885	0.8954	0.8145
	Mean Square Error	0.1645	0.1451	0.1347
	Signal to Noise Ratio	4.1802	4.3540	5.4789
	Image Quality Index	0.8763	0.9514	0.8974
STARFISH	Average Difference	0.3664	0.2198	0.1074
	Maximum Distance	0.4664	0.9198	0.8741
	Image Fidelity	0.8348	0.5846	0.9844
	Mean Square Error	0.2138	0.9132	0.0124
	Signal to Noise Ratio	0.8383	0.8404	2.1478
	Image Quality Index	0.4710	0.7250	0.6259
TIGER	Average Difference	0.3350	0.5581	0.3512
	Maximum Distance	0.4925	0.6547	0.7514
	Image Fidelity	0.9882	0.9981	0.9981
	Mean Square Error	0.0038	0.0012	0.0014
	Signal to Noise Ratio	11.1494	14.521	18.4521
	Image Quality Index	0.9869	0.9914	0.9913

VII. CONCLUSIONS

This paper introduces the novel image segmentation algorithm for images having lapty kurtic distributed pixel intensities of the image regions. For the grey images the pixel intensity characterizes the feature of the image regions. Here the logistic probability model is considered for characterizing the whole image. The logistic model is capable of portraying lapty kurtic. The image regions having lapty kurtic image features. It is also capable of representing different types of image regions. The experimentation with five randomly chosen images from Berkeley image data base reveals that the proposed algorithm efficiently segment the images. This is evident from the computed segmentation quality metrics. The comparative study of the proposed algorithm with that of GMM has established that the proposed algorithm is superior. This is also evident from the computed image quality metrics. It is also observed the hierarchal clustering algorithm in initializing the parameters further improves the efficiency of the segmentation than that of the K-means algorithm for initialization. The proposed algorithm is also useful for image analysis arising at medical diagnostic, remote sensing, video analysis. It is possible to consider image segmentations for color images using mixture of multivariate logistic model, which will be discussed elsewhere.

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