Performance Evaluation of Image Segmentation Method based on Doubly Truncated Generalized Laplace Mixture Model and Hierarchical Clustering

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Abstract—The present paper aims at performance evaluation of Doubly Truncated Generalized Laplace Mixture Model and Hierarchical clustering (DTGLMM-H) for image analysis concerned to various practical applications like security, surveillance, medical diagnostics and other areas. Among the many algorithms designed and developed for image segmentation the dominance of Gaussian Mixture Model (GMM) has been predominant which has the major drawback of suiting to a particular kind of data. Therefore the present work aims at development of DTGLMM-H algorithm which can be suitable for wide variety of applications and data. Performance evaluation of the developed algorithm has been done through various measures like Probabilistic Rand index (PRI), Global Consistency Error (GCE) and Variation of Information (VOI). During the current work case studies for various different images having pixel intensities has been carried out and the obtained results indicate the superiority of the developed algorithm for improved image segmentation.

Index Terms—Image segmentation, Generalized Laplace Mixture Model, doubly truncated generalized Laplace Mixture Model, EM algorithm.

I. INTRODUCTION

Image segmentation aims at identifying the regions of interest in an image or annotating the data of an image. It is the process to classify an image into several clusters according to the feature of image. Image segmentation techniques are based on some pixel or region similarity measures in relation to their local neighborhood. Segmentation techniques are broadly classified as region based, edge based, threshold based and model based [1-4]. Among these model based segmentation algorithms are found to be efficient compared to other [5]. In model based, entire image is viewed as a collection of image regions and each image region is characterized by a probability distribution function of pixels.

The pixel intensity is considered as a feature component of the image. The pixel intensities in image may be meso kurtic, platy kurtic, lepto kurtic, symmetric and asymmetric. The efficiency of segmentation algorithm depends on probability distribution followed by the pixels in an image.

Much work has been reported considering the pixel intensities follow a Gaussian distribution and variates of finite GMM. Yunjie Chen et al[6] analyzed Gaussian Mixture Model based on Non Local Information for brain MR images segmentation. Legendre polynomials were used to fit and merged to the EM framework and non local information was also used to preserve the geometrical edges information. Karim Kalti et al[7] analyzed an image segmentation method based on Gaussian Mixture model and modified FCM Algorithm. The classification was made on the basis of adaptive distance which privileged the one or the other features according to the spatial position of the pixel in the image. Zhaoxia Fu et al [8] proposed an image segmentation method which used Gaussian Mixture Models to model
the original image and transforms the segmentation problem into maximum likelihood parameter estimation by expectation-maximization (EM algorithm) and classify the pixels in image. The application of GMM is accurate and successful for all types of data except leptokurtic. To overcome this drawback generalization of Gaussian mixture models with respect to kurtosis is considered. Laplace probability model serves as a alternate to Gaussian distribution with respect to platykurtic, leptokurtic and asymmetric data. Srinivasa Rao et al [9] generalized the laplace distribution as generalized Laplace distribution. Jyothirmayi et al [10] later developed and analyzed the generalised Laplace mixture model (GLMM) for image segmentation. In these algorithms the range of pixel intensities was assumed as \([-\infty, \infty]\).

The developed model was integrated with hierarchical clustering method and used for image segmentation of images which are having platykurtic and leptokurtic nature. Hierarchical clustering and moment method of estimation was used for initialization of parameters. As an extension to the previous works, within the current work an attempt is made to extend the GLMM as Doubly Truncated GLMM (DTGLMM) by truncating the range of pixel intensity values within a specified range. Performance evaluation of the developed model has been carried out by means of analysis of various different categories of images as case studies.

II. PROPOSED WORK

In this paper an algorithm DTGLMM-H has been proposed for image segmentation. It is assumed that the whole image is collection of image regions in which the pixel intensity of each region follows a generalized laplace distribution. The parameters mean, variance of DTGLMM are estimated through EM algorithm. Initialization of the parameters is obtained by hierarchical clustering. Image analysis with the developed algorithm is performed on five images from Berkeley image data set and compared with existing algorithms available in the literature.

A. Doubly Truncated Generalized Laplace Distribution

An image is considered as a collection of image regions for segmentation algorithms. Each image is quantized by pixel intensities. The pixel intensity \(z=f(x,y)\) is a random variable for any given point in image region. The pixel intensities within the region are assumed to have an infinite range. But in any image the pixel intensity lie between two values. Assuming that the pixel intensity lie between \('a'\) and \('b'\), the probability density function of the pixel intensity is given by

\[
f(x, \mu, \sigma^2) = \begin{cases} \frac{\mu(x - \mu) r^{r-1} e^{-|x-\mu|/\sigma}}{2\sigma \sum_k \left( \begin{smallmatrix} r \\ k \end{smallmatrix} \right) \sigma^k x^k e^{-|x|/\sigma} dx} & \text{where } a < x < b, a \mu < b, \sigma > 0 
\end{cases}
\]  

(1)

This can also be represented as

\[
f(x, \mu, \sigma^2) = \frac{\mu(x - \mu) r^{r-1} e^{-|x-\mu|/\sigma}}{2\sigma \sum_k \left( \begin{smallmatrix} r \\ k \end{smallmatrix} \right) \sigma^k x^k e^{-|x|/\sigma}}
\]

It is supposed that entire image is collection of several image regions where each image region’s pixel intensities are characterized by doubly truncated generalized Laplace probability model. The probability density function of pixel intensities in whole image is of the form

\[
p(x) = \sum_{i=1}^{k} \alpha_i f_i(x_n, \mu_i, \sigma_i^2)
\]  

(2)

Where \(k\) is the number of regions, \(0 \leq \alpha_i \leq 1\) are weights such that \(\sum \alpha_i = 1\) and \(\alpha_i\) is the weight associated with \(i^{th}\) region in the whole image and \(f_i(x, \mu, \sigma^2)\) is the probability density function of Generalized Laplace distribution of \(i^{th}\) image region and is as given in equation (1)

The mean of the distribution is

\[
E(X) = \int_0^\infty x f(x) dx = \mu + \sum_{k=0}^r \binom{r}{k} \sigma^k \int_0^\infty x^k e^{-|x|/\sigma} dx
\]

(3)

The variance of the distribution is

\[
\text{var}(x) \text{=} \frac{1}{n} \sum_{i=1}^{n} \text{var}(z_i) = \frac{\mu^2 q + (-1)^q \sigma^q \sum_{k=0}^{(q+1)} \binom{r}{k} \sigma^k \int_0^\infty x^k e^{-|x|/\sigma} dx}{\sum_{k=0}^{(q+1)} \binom{r}{k} \sigma^k \int_0^\infty x^k e^{-|x|/\sigma} dx}
\]

(4)
B. Estimation of the Model Parameters By EM Algorithm

To estimate the model parameters, EM algorithm is utilized by maximizing the expected likelihood function. It is assumed that the intensity of pixel in image region follows a new Laplace distribution and whole image is characterized with a finite mixture of new generalized Laplace distributions. To get accurate result doubly truncated generalized Laplace distribution is well suited where range of pixel intensities is assumed to be finite. Its probability distribution function is given in equation 2.

The likelihood function of observations $x_1, x_2, \ldots, x_n$ is

$$L(\theta) = \prod_{i=1}^{N} p(x_i, \theta^i)$$

(i.e) $L(\theta) = \prod_{i=1}^{N} (\sum_{k=1}^{K} \alpha_k f_i(x_i, \mu_k, \sigma_k^2))$

Log $L(\theta) = \sum_{i=1}^{N} \log (\sum_{k=1}^{K} \alpha_k f_i(x_i, \mu_k, \sigma_k^2))$

where

$$\theta = \{\mu, \sigma^2, \alpha, i=1,2,..k\}$$

$$\log \sum_{i=1}^{N} \log \left( \frac{r^2 + (x - \mu)^2}{\sigma^2} e^{-\frac{|x - \mu|}{\sigma}} \right)$$

(5)

E Step: In the E Step the expectation value of log $L(\theta)$ with respect to initial parameter $\theta^0$ is

$$Q(\theta; \theta^0) = E_q[log L(\theta)]$$

(7)

$$P(x_i, \theta^i) = \sum_{k=1}^{K} \alpha_k f_i(x_i, \mu_k, \sigma_k^2)$$

Log $L(\theta) = \sum_{s=1}^{N} \log (\sum_{k=1}^{K} \alpha_k f_i(x_i, \theta^i))$

(8)

The conditional probability of $x_s$ belonging to region $k$ is

$$Q(\theta; \theta^0) = \sum_{s=1}^{K} \sum_{i=1}^{N} \alpha_k f_i(x_i, \theta^i) (\log f_i(x_i, \theta^i) + \log \alpha_k)$$

(9)

$T_i(x_i, \theta^i) = \frac{\alpha_k f_i(x_i, \theta^i)}{\sum_{k=1}^{K} \alpha_k f_i(x_i, \theta^i)}$

$Q(\theta; \theta^0) = \sum_{s=1}^{K} \sum_{i=1}^{N} T_i(x_i, \theta^i) (\log f_i(x_i, \theta^i) + \log \alpha_k)$

(10)

M Step: To get estimation of parameters, maximize $Q(\theta; \theta^0)$ such that $\sum \alpha_k = 1$.

Using Lagrange type function and maximizing

$$\alpha_k = \frac{1}{n} \sum_{s=1}^{N} T_i(x_i, \theta^i)$$

For updating the parameter $\mu_i$, $i=1,2..k$

$$Q(\theta; \theta^0) = E[log L(\theta; \theta^0)]$$

(11)

$$\frac{\partial}{\partial \mu_i} Q(\theta; \theta^0) = 0$$

This implies

$$\frac{\partial}{\partial \mu_i} \sum_{s=1}^{K} \sum_{i=1}^{N} T_i(x_i, \theta^0) \left[ \log \left( \frac{(r^2 + (x - \mu)^2)}{\sigma^2} e^{-\frac{|x - \mu|}{\sigma}} \right) \right]$$

$$= 0$$

(12)

$$\sum_{s=1}^{K} \sum_{i=1}^{N} T_i(x_i, \theta^0) \left[ \frac{2r(x - \mu)}{\sigma^2} e^{-\frac{|x - \mu|}{\sigma}} \right]$$

$$= 0$$

(13)

For updating $\sigma_i^2$ differentiate $Q(\theta; \theta^0)$ w.r.t $\sigma_i^2$ and equate to $0$
\[
\frac{\partial}{\partial \sigma_i^2} \sum_{i=1}^{k} \sum_{x_{si}} T_i(x_{si}, \theta^l) \left[ \log \left( \frac{\mu - \mu_i}{\sigma_i^2} \right) - \frac{x_{si} - \mu_i}{\sigma_i} \right] \right]
\sum_{k=0}^{r} \left( \frac{b - \mu_i}{\sigma_i^2} \cdot e^{-\frac{b - \mu_i}{\sigma_i^2}} \right) \right) + \log(\alpha_i) \right] = 0
\]

This implies
\[
\frac{\partial}{\partial \sigma_i^2} \left[ \sum_{i=1}^{k} \sum_{x_{si}} T_i(x_{si}, \theta^l) \left[ \log \left( \frac{r^2 + \frac{(x_{si} - \mu_i)^2}{\sigma_i^2}}{2\sigma_i^2} \right) - \frac{x_{si} - \mu_i}{\sigma_i} \right] \right] - \left( \frac{b - \mu_i}{\sigma_i^2} \right) \cdot \frac{b - \mu_i}{\sigma_i^2} \cdot e^{-\frac{b - \mu_i}{\sigma_i^2}} \cdot \frac{b - \mu_i}{\sigma_i^2} \cdot e^{-\frac{b - \mu_i}{\sigma_i^2}} \right) + \log(\alpha_i) \right] \left[ \log \left( \frac{r^2 + \frac{(x_{si} - \mu_i)^2}{\sigma_i^2}}{2\sigma_i^2} \right) - \frac{x_{si} - \mu_i}{\sigma_i} \right] \right] \right] = 0
\]

\[
\sum_{x_{si}} T_i(x_{si}, \theta^l) \left[ \log \left( \frac{r^2 + \frac{(x_{si} - \mu_i)^2}{\sigma_i^2}}{2\sigma_i^2} \right) - \frac{x_{si} - \mu_i}{\sigma_i} \right] = 0
\]

\[
\sum_{i=1}^{k} \sum_{x_{si}} T_i(x_{si}, \theta^l) \left[ \log \left( \frac{r^2 + \frac{(x_{si} - \mu_i)^2}{\sigma_i^2}}{2\sigma_i^2} \right) - \frac{x_{si} - \mu_i}{\sigma_i} \right] = 0
\]

\[
T_i(x_{si}, \theta^l) = \frac{a_{i1}^{l+1} f_i(x_{si}, \theta^l)}{\sum_{i=1}^{k} a_{i1}^{l+1} f_i(x_{si}, \theta^l)}
\]

(15)

solving the equations 13 and 15 we can get the final estimates of the parameters \( \mu_i \) and \( \sigma_i^2 \).

C. Initialization of the Parameters By Hierarchical clustering algorithm

\[
\beta_2 = \left[ \frac{\sum_{i=0}^{k} r^{2(r-1)} \sum_{q=0}^{r} \frac{r^q}{q!} \left( \frac{\mu - \mu_i}{\sigma_i} \right)^{2q} \sigma_i^2 \left[ \left( \frac{2k+q+1}{\alpha} \right) - \left( \frac{2k+q+1}{\alpha} \right)^2 \right] \gamma(2k+q+1) \right]}{\sum_{i=0}^{k} r^{2(r-1)} \sum_{q=0}^{r} \frac{r^q}{q!} \left( \frac{\mu - \mu_i}{\sigma_i} \right)^{2q} \sigma_i^2 \left[ \left( \frac{2k+q+1}{\alpha} \right) - \left( \frac{2k+q+1}{\alpha} \right)^2 \right] \gamma(2k+q+1) \right] \gamma(2k+q+1) \right] \right]
\]

(16)

\[
\bar{x} = \mu + \left[ \frac{\sum_{i=0}^{k} r^{2(r-1)} \sum_{q=0}^{r} \frac{r^q}{q!} \left( \frac{\mu - \mu_i}{\sigma_i} \right)^{2q} \sigma_i^2 \left[ \left( \frac{2k+q+1}{\alpha} \right) - \left( \frac{2k+q+1}{\alpha} \right)^2 \right] \gamma(2k+q+1) \right]}{\sum_{i=0}^{k} r^{2(r-1)} \sum_{q=0}^{r} \frac{r^q}{q!} \left( \frac{\mu - \mu_i}{\sigma_i} \right)^{2q} \sigma_i^2 \left[ \left( \frac{2k+q+1}{\alpha} \right) - \left( \frac{2k+q+1}{\alpha} \right)^2 \right] \gamma(2k+q+1) \right] \gamma(2k+q+1) \right] \right]
\]

(17)

and \( \sigma_i^2 \) is

\[
\sigma_i^2 = \left[ \frac{\sum_{i=0}^{k} r^{2(r-1)} \sum_{q=0}^{r} \frac{r^q}{q!} \left( \frac{\mu - \mu_i}{\sigma_i} \right)^{2q} \sigma_i^2 \left[ \left( \frac{2k+q+1}{\alpha} \right) - \left( \frac{2k+q+1}{\alpha} \right)^2 \right] \gamma(2k+q+1) \right]}{\sum_{i=0}^{k} r^{2(r-1)} \sum_{q=0}^{r} \frac{r^q}{q!} \left( \frac{\mu - \mu_i}{\sigma_i} \right)^{2q} \sigma_i^2 \left[ \left( \frac{2k+q+1}{\alpha} \right) - \left( \frac{2k+q+1}{\alpha} \right)^2 \right] \gamma(2k+q+1) \right] \gamma(2k+q+1) \right] \right]
\]

(18)

Solving equations 16, 17 and 18 simultaneously by Newton Raphson Method the parameters \( \mu_i \) and \( \sigma_i^2 \) are obtained. With these initial estimates final estimates are obtained through EM algorithm as illustrated in section B.

D. Segmentation Algorithm

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Once the final estimates of parameters are obtained, next step is to segment the image by assigning the pixels to segments. This is achieved through the following segmentation algorithm.

Step 1: Attain the number of image segments using hierarchical clustering algorithm.

Step 2: Obtain the initial estimates of model parameters using hierarchical clustering.

Step 3: Using the EM algorithm obtain the refined estimates of the model parameters $\alpha_i, \mu_i, \sigma_i$ for $i=1,2,\ldots,K$.

Step 4: Assign each pixel to corresponding $j^{th}$ segment according to maximum likelihood of the segment $L_j$. The pixel $z_i$ is assigned to the $j^{th}$ segment for which $L$ is maximum.

$$L = \max_{j} \left( \frac{\left(\frac{e^{(x-\mu_i)^2/\sigma_i^2}}{\sigma_i \sqrt{2\pi}} \right)^j e^{-\frac{x^2}{2\sigma_i^2}}}{\sigma_i \sqrt{2\pi}} \right)$$  \hspace{1cm} (19)

III. EXPERIMENTATION AND RESULTS

For experimentation five images randomly were taken from Berkeley image dataset (www.eecs.berkeley.edu/Research/Projects/CS/vision/bds/BSDS300/html/dataset/images.html). The pixel intensity values in image are chosen as feature of the image assuming that they follow generalized Laplace distribution. Image consists of K image regions and initial value of K is obtained by histogram of pixel intensities. The five images and their respective histograms are shown in Figure 1.

![Fig.1. Images and their Histograms.](image-url)

Table 1. Estimation of parameters for Image1

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimation of Initial Parameters By Hierarchical Clustering</th>
<th>Estimation of Final Parameters by EM Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_i$</td>
<td>0.33 0.33 0.33</td>
<td>0.136 0.985 0.150</td>
</tr>
<tr>
<td>$\mu_i$</td>
<td>102.72 244.9 148.3</td>
<td>251.9 198.3 261.1</td>
</tr>
<tr>
<td>$\sigma_i$</td>
<td>10.79 6.90 15.29</td>
<td>13.37 51.31 40.74</td>
</tr>
</tbody>
</table>

$a=0$  
$b=255$

Table 2. Estimation of parameters for Image2

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimation of Initial Parameters By Hierarchical Clustering</th>
<th>Estimation of Final Parameters by EM Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_i$</td>
<td>0.33 0.33 0.33</td>
<td>0.43 0.43 0.13</td>
</tr>
<tr>
<td>$\mu_i$</td>
<td>185.37 151.79 69.28</td>
<td>190.55 48.16 111.8</td>
</tr>
<tr>
<td>$\sigma_i$</td>
<td>9.42 8.95 11.13</td>
<td>15.53 11.30 18.2</td>
</tr>
</tbody>
</table>

$a=34$  
$b=254$

Table 3. Estimation of parameters for Image3

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimation of Initial Parameters By Hierarchical Clustering</th>
<th>Estimation of Final Parameters by EM Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_i$</td>
<td>0.33 0.33 0.33</td>
<td>0.352 -0.021 0.668</td>
</tr>
<tr>
<td>$\mu_i$</td>
<td>144.5 53.46 180.8</td>
<td>170.5 49.37 194.8</td>
</tr>
<tr>
<td>$\sigma_i$</td>
<td>7.21 16.03 4.94</td>
<td>18.53 18.30 15.24</td>
</tr>
</tbody>
</table>

$a=7$  
$b=187$

Table 4. Estimation of parameters for Image4

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimation of Initial Parameters By Hierarchical Clustering</th>
<th>Estimation of Final Parameters by EM Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_i$</td>
<td>0.33 0.33 0.33</td>
<td>0.7666 -0.0018 0.2343</td>
</tr>
<tr>
<td>$\mu_i$</td>
<td>242 34.33 179.79</td>
<td>193.86 58.16 159.80</td>
</tr>
<tr>
<td>$\sigma_i$</td>
<td>12.63 5.85 18.36</td>
<td>10.09 13.70 20.27</td>
</tr>
</tbody>
</table>

$a=30$  
$b=255$
Table 5. Estimation of parameters for Image5

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimation of Initial Parameters by Hierarchical Clustering</th>
<th>Estimation of Final Parameters by EM Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_1$</td>
<td>0.33</td>
<td>0.18</td>
</tr>
<tr>
<td>$\mu_1$</td>
<td>110.91</td>
<td>24.05</td>
</tr>
<tr>
<td>$\sigma_1$</td>
<td>14.39</td>
<td>10.53</td>
</tr>
</tbody>
</table>

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

The estimated probability density function of the pixel intensities of the image1 is

$$f(x, \theta^1) = \frac{1}{26.74} \left(1 + \frac{(x-251.93)^2}{13.37^2}\right)^{r} e^{-\frac{|x-251.93|}{13.37}} + \frac{1}{102.62} \left(1 + \frac{(x-198.30)^2}{51.31^2}\right)^{r} e^{-\frac{|x-198.30|}{51.31}} + \frac{1}{81.48} \left(1 + \frac{(x-261.12)^2}{40.74^2}\right)^{r} e^{-\frac{|x-261.12|}{40.74}}$$

The estimated probability density function of the pixel intensities of the image2 is

$$f(x, \theta^2) = \frac{1}{31.06} \left(1 + \frac{(x-190.55)^2}{15.53^2}\right)^{r} e^{-\frac{|x-190.55|}{15.53}} + \frac{1}{22.6} \left(1 + \frac{(x-48.16)^2}{11.30^2}\right)^{r} e^{-\frac{|x-48.16|}{11.30}} + \frac{1}{36.4} \left(1 + \frac{(x-111.8)^2}{18.2^2}\right)^{r} e^{-\frac{|x-111.8|}{18.2}}$$

The estimated probability density function of the pixel intensities of the image3 is

$$f(x, \theta^3) = \frac{1}{37.06} \left(1 + \frac{(x-170.55)^2}{18.53^2}\right)^{r} e^{-\frac{|x-170.55|}{18.53}} + \frac{1}{36.6} \left(1 + \frac{(x-49.37)^2}{18.3^2}\right)^{r} e^{-\frac{|x-49.37|}{18.3}} + \frac{1}{30.48} \left(1 + \frac{(x-194.80)^2}{15.24^2}\right)^{r} e^{-\frac{|x-194.80|}{15.24}}$$

The estimated probability density function of the pixel intensities of the image4 is

$$f(x, \theta^4) = \frac{1}{20.18} \left(1 + \frac{(x-193.8)^2}{10.09^2}\right)^{r} e^{-\frac{|x-193.8|}{10.09}} + \frac{1}{27.4} \left(1 + \frac{(x-58.16)^2}{13.7^2}\right)^{r} e^{-\frac{|x-58.16|}{13.7}} + \frac{1}{40.54} \left(1 + \frac{(x-159.80)^2}{20.27^2}\right)^{r} e^{-\frac{|x-159.80|}{20.27}}$$

The estimated probability density function of the pixel intensities of the image5 is

$$f(x, \theta^5) = \frac{1}{21.06} \left(1 + \frac{(x-24.05)^2}{10.53^2}\right)^{r} e^{-\frac{|x-24.05|}{10.53}} + \frac{1}{28.60} \left(1 + \frac{(x-116.42)^2}{14.30^2}\right)^{r} e^{-\frac{|x-116.42|}{14.30}} + \frac{1}{26.52} \left(1 + \frac{(x-72.04)^2}{13.26^2}\right)^{r}$$

Using the probability density function and segmentation algorithm, image segmentation is performed for following images. The original images and segmented images are shown in Figure 2.

Fig. 2. Original Image and Segmented Image

IV. PERFORMANCE MEASURES

Once the image segmentation has been performed, its performance has been measured by calculating the performance metrics like probabilistic rand index (PRI) given by Unnikrishnan R et al (2007), global consistency error(GCE) given BY Martin D. and et al and variation of information (VOI) given by Meila M(2005). The standard criteria for metrics is that PRI and GCE values must lie in range 0 to 1 while VOI can take value as big as possible. The performance metrics for image segmentation method based on doubly truncated generalized mixture model using hierarchical clustering.
(DTGLMM-H) is shown in Table 6 and compared with segmentation method based on GMM, GLMM using K-means (GLMM-K), GLMM using Hierarchical clustering (GLMM-H) and doubly truncated generalized mixture model using K-means algorithm (DTGLMM-K).

From Table 6 it is observed that the proposed method satisfies the standard criteria for the performance measures PRI, GCE and VOI. The performance metrics are compared with GMM, GLMM-K, GLMM-H and DTGLMM-K and presented in Figure 3.

The image can also be reconstructed using the DTGLMM-H has performed well when compared with other methods.

The original images and reconstructed images using developed segmentation algorithm are presented in Figure 4.

<table>
<thead>
<tr>
<th>Table 6: Performance Measures</th>
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<tbody>
<tr>
<td><strong>Image</strong></td>
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<td><strong>Image4</strong></td>
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V. CONCLUSION

This paper addresses the image segmentation method based on doubly truncated generalized Laplace distribution mixture model and hierarchical clustering. The feature vector associated with the image region is characterized by truncated generalized Laplace distribution which improves Laplace and generalized laplace distributions as limiting cases. The doubly truncated generalized laplace distribution includes a spectrum of probability models which may be mesokurtic, platykurtic, leptokurtic, symmetric and asymmetric. The effect of truncation on probability model has a significant influence since in reality the pixel intensities are having finite range. The model parameters are estimated by deriving updated equations of the scale and location parameters. The shape parameter is estimated using sample kurtosis. The initialization of parameter is carried using hierarchical clustering for initial segmentation for whole image and moment methods of estimation. The performance of the algorithm is analyzed through experimentation on randomly chosen five images from Berkeley data set. The performance measures such as PRI, GCE and VOI revealed that this algorithm perform better than the earlier algorithms. This may be due to the effect of truncation used for modeling feature vector. The hierarchical clustering algorithm used for initialization of parameters reduces the computational complexities and convergence of the EM algorithm. The proposed algorithm is much useful for analyzing images arising at several domains of applications. It is possible to extend this image segmentation method for color images considering a 3-dimensional feature vector which will be taken up elsewhere.

REFERENCES


Authors’ Profiles

T. Jyothirmayi is presently working as Assistant Professor in the department of Computer Science and Engineering, GIT, GITAM University, Visakhapatnam. She presented research papers in national and international conferences and journals of good repute. She guided several students for Project work in department of Computer Science Engineering. Her current research interests include image processing and data mining.

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