International Journal of Computational Vision and Biomechanics
Vol. 3 No. 1 (January-June, 2017)

Unsupervised Image Segmentation Based on Finite Generalized Gaussian Mixture Model with Hierarchical Clustering

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In this paper a new Image Segmentation method based on Finite Generalized Gaussian Mixture Distribution with Hierarchical Clustering is developed. In this method, it is considered that the pixel intensities inside each image region follow a Generalized Gaussian Distribution and the pixel intensities in the entire image are characterized by a Finite Generalized Gaussian Mixture Distribution. Here the number of components (Image Regions) in the image is obtained through Hierarchical Clustering method, and the model parameters are estimated by using EM algorithm. The segmentation of the pixel intensities is carried by maximizing the component likelihood function. The performance of the developed method is demonstrated through SIX images namely, SUNSET, BULL, MAN, HILLS, WOMEN , LOTUS and obtaining the Image Quality Metrics like, Average Difference, Maximum Distance, Image Fidelity, Mean Square Error, Signal to Noise Ratio and Image Quality Index. It is observed that in all the above Image Quality Metrics this algorithm is superior to the existing Image Segmentation algorithms based on Finite Gaussian Mixture Model and Finite Truncated Gaussian Mixture Model. It is also interesting to note that this algorithm also includes the earlier segmentation algorithms as particular cases for specific values of the shape parameters.

Keywords: *Image Segmentation, Finite Generalized Gaussian Mixture Distribution, EM algorithm, Image Quality Metrics, Shape Parameter*

1. INTRODUCTION

Image Segmentation plays a dominant role in Image Processing and Image Retrieval. Recently, much emphasis was given for Image Segmentation and Image Analysis. S. K. Pal and N.R.Pal (1993), Jahne (1995), Cheng *et al.* (2001) have presented a comprehensive discussion on Image Segmentation. Among the different Image Segmentation methods, Model Based Image Segmentation is more efficient compared to the Non-Parametric methods of Image Segmentation. With this model based approach to parametric segmentation (clustering) as opposed to non-parametric methods, issues like the selection of the number of clusters or the assessment of the validity of a given model can be addressed in a principled and formal way (Mano A. T. Figueiredo *et al.* (2002)) In the non-parametric methods such as K-Means and Mean Shift methods that are based on some useful heuristics performed well if the heuristic match the data, for example, K-Means provide good results when the data is blob like and the agglomerative methods succeeds when the clusters are dense and if there is no noise. However, those usually observable in typical images results in failure of these methods.

(Marco Andereeto *et al.* (2007). In Model Based Image Segmentation each pixel is characterized by the pixel intensity which are random because of various Stochastic factors like, environment, moisture, temperature etc., Hence the entire image is considered to be a collection of several image regions. The efficiency of the segmentation algorithm is based on the suitable probability distribution ascribed to the pixel intensities in the entire image. In model based image segmentation, it is customary to assume that the pixel intensities in an image region follow a Gaussian Distribution and the pixel intensities in the entire image are characterized with a Finite Mixture Distribution. Much work has been reported regarding image segmentation based on Finite Gaussian Mixture Model (Yamazaki *et al.* (1998), T. Lie *et al.* (1993), N. Nasios *et al.* (2006), Z. H. Zhang *et al.* (2003)). However, in many practical situations arising at places like, Medical Imaging, Robotics, Photo Copiers etc., the pixel intensities inside the image region may not be mesokurtic. To have a closer approximation to the realistic situations, it is needed to Generalize the image segmentation algorithms with a more General Distribution, which includes the Finite Gaussian Mixture Model as a particular case. Hence in this paper, we develop and analyze an image segmentation method based on Finite Generalized Gaussian Distribution. The Generalized Gaussian Distribution includes the Gaussian and Laplace distributions as particular cases. In addition to the location and scale parameters, the Generalized Gaussian Distribution is having another parameter (Shape Parameter) 'P' which measures the peakeness of the distribution, Sharif. K. *et al.* (1995) has utilized the Generalized Gaussian Distribution for modeling the atmospheric noise sub-band encoding of audio and video signals, W. U. H. C. Y. Principe J. (1998) used the distribution for signal separation, Chois *et al.* (2000) have used the distribution for impulse noise detection. Very little work has been reported regarding image segmentation based on Finite Generalized Gaussian Mixture Model. We utilize the Hierarchical Clustering algorithm for identifying the number of image regions and for obtaining the initial estimates of the model parameters. The model parameters in each image region are refined by using EM algorithm. By maximizing the component likelihood function, each image pixel is retrieved to its region. The performance of this method is evaluated through Image Quality Metrics like Average Difference, Maximum Distance, Image Fidelity, Mean Square Error, Signal to Noise Ratio, Image Quality Index. A comparative study of this method with the earlier method is also presented.

2. GENERALIZED GAUSSIAN DISTRIBUTION

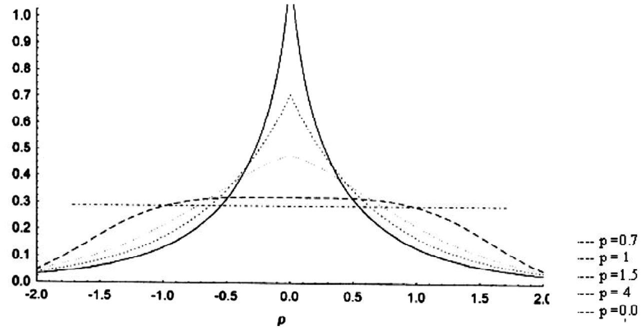
In this section we briefly discuss the probability distribution and its properties used in the image segmentation algorithm. Let the pixel intensities in the entire image be a Random Variable and follow a Finite Generalized Gaussian Mixture Distribution. It is also assumed that the entire image is a collection of "K' image regions, then the pixel intensities in each image region follow a Generalized Gaussian Distribution. The probability density function of pixel intensity in a region is given by

$$f(z \mid \mu, \sigma, P) = \frac{1}{2\Gamma(1+\frac{1}{P})A(P,\sigma)} e^{-\left|\frac{(Z_i - \mu_i)}{A(P,\sigma)}\right|^P}$$

$$\text{where} \quad \sigma > 0,\ A(P,\sigma) = \left[\frac{\sigma^2 \Gamma(1/P)}{\Gamma(3/P)}\right]^{\frac{1}{2}} \qquad -\infty < z < \infty,$$

$$-\infty < \mu < \infty, P > 0 \qquad (1)$$

The parameter μ is the mean, the function $A(P, \sigma)$ is an scaling factor which allows that the $\text{Var}(Z) = \sigma^2$, and 'P' is the shape parameter. When $P = 1$, the corresponding Generalized Gaussian Distribution corresponds to Laplacian or Doubly Exponential Distribution. When P = 2, the corresponding Generalized Gaussian Distribution corresponds to a Gaussian Distribution. In limiting cases $P \to +\infty$ converge to a uniform distribution in $(\mu - \sqrt{3}\sigma, \mu + \sqrt{3}\sigma)$ and when $P \to 0$, the distribution become a degenerate one in $Z = \mu$. The different shapes of frequency curves of the Generalized Gaussian Distribution are shown in figure 1.



Generalized Gaussian pdf's for different values of p.

Figure 1

3. DETERIMINATION OF NUMBER OF IMAGE REGIONS

In this section we develop the Image Segmentation algorithm using Finite Generalized Gaussian Mixture Model and Hierarchical Algorithm (S. C. Johnson (1967)). The pixel intensities inside the image region are random and follow a probability distribution. Hence the pixel intensities of the entire image follow a mixture distribution. In image segmentation the number of image regions ('K') is required to identify the mixture model ascribed to the pixel intensities. The utilized Hierarchical Clustering algorithm is having computational complexity of $O(n^2)$, which might limit the applicability if the overall segmentation algorithm to large images, this may be a drawback for small images. For determining the number of image regions we consider the following Hierarchical Clustering method (S. C. Johnson (1967)).

Step 1: Start by assigning each item to a segment, so that if you have N items, you now have N segments, each containing just one item. The distances (similarities) between the segments is as the distances (similarities) between the items they contain.

Step 2: Find the closest (most similar) pair of segments and merge them into a single segment, so that now you have one segment less. Compute distances (similarities) between the new segment and each of the old segments.

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

Step 3 can be done with single-linkage method of clustering In Single-Linkage segmenting (also called the connectedness or minimum method), we consider the distance between one segment and another segment to be equal to the shortest distance from any member of one segment to any member of the other segment. If the data consist of similarities, we consider the similarity between one segment and another segment to be equal to the greatest similarity from any member of one segment to any member of the other segment.

The algorithm is an agglomerative scheme that erases rows and columns in the proximity matrix as old segments are merged into new ones.

The $N*N$ proximity matrix is $D = [d(i,j)]$. The segments are assigned sequence numbers 0,1.., (n-1) and $L(k)$ is the level of the K^{th} segment. A segment with sequence number m is denoted (m) and the proximity between segments (r) and (s) is denoted as d [(r), (s)].

The algorithm is composed of the following steps:

(1) Begin with the disjoint segment having level $L(0) = 0$ and sequence number $m = 0$.

(2) Find the least dissimilar pair of segments in the current segment; say pair (r), (s), where the minimum is over all pairs of segments in the current segment.

(3) Increment the sequence number: $m = m + 1$. Merge segments (r) and (s) into a single segment to form the next segmenting m. Set the level of this segmenting to $L(m) = d[(r), (s)]$

(4) Update the proximity matrix, D, by deleting the rows and columns corresponding to segments (r) and (s) and adding a row and column corresponding to the newly formed segment. The proximity between the new segment, denoted (r, s) and old segment (K) is defined in this way.

$d[(K), (r, s)] = \min d[(K), (r)], d[(K), (s)]$

(5) If all objects are in one cluster, stop. Else, go to step 2.

4. ESTIMATION OF THE MODEL PARAMETERS THROUGH EM ALGORITHM

In this section we obtain the estimates of the model parameters through EM algorithm. Here it is assumed that the pixel intensities in each image region follow a Generalized Gaussian Distribution with probability density functions of the form

$$f(z \mid \mu, \sigma, P) = \frac{1}{2\Gamma(1+\frac{1}{P})A(P,\sigma)} e^{-\left|\frac{(Z_i-\mu_i)}{A(P,\sigma)}\right|^P}$$

$$\text{Where } \sigma > 0,\ A(P,\sigma) = \left[\frac{\sigma^2\Gamma(1/P)}{\Gamma(3/P)}\right]^{\frac{1}{2}} \tag{2}$$

As a result of this, the pixel intensities in the entire image follow a Finite Mixture of Generalized Gaussian Distribution with Probability density function

$$h(z, \theta) = \Sigma\, \alpha_i f_i(z_s, \theta_i) \tag{3}$$

Then the likelihood function of the pixel intensities are

$$L(\theta) = \pi_{s=1}^{N}\left(\sum_{l=1}^{K}\alpha_i f_i(z_s,\theta_i)\right) \tag{4}$$

$$\pi_{i=1}^{N}\left(\sum_{i=1}^{K}\alpha_i \frac{1}{2\Gamma(1+\frac{1}{P})A(P,\sigma)} e^{-\left|\frac{(Z_i-\mu_i)}{A(P,\sigma)}\right|^P}\right) \text{ where } A(P,\sigma) = \left[\frac{\sigma^2\Gamma(1/P)}{\Gamma(3/P)}\right]^{\frac{1}{2}} \tag{5}$$

This implies $L(\theta) = \sum_{l=1}^{N}\log h(z,\theta) =$

$$h(z,\theta) = \sum_{s=1}^{N}\log\sum_{i=1}^{K}\alpha_i f_i(z_s,\theta_i)$$

$$= \sum_{s=1}^{N}\log\left(\sum_{i=1}^{K}\alpha_i \frac{1}{2\Gamma(1+\frac{1}{P})A(P,\sigma)} e^{-\left|\frac{(Z_i-\mu_i)}{A(P,\sigma)}\right|^P}\right) \tag{6}$$

We have to find the parameter α_i, μ_i and σ_i for $i = 1,2,$—K, maximizing the likelihood function (or) Log likelihood function. Here the shape parameter 'P' is estimated by the procedure given by J. Armando Dominguez *et al.* (2003) and also we assume that shape parameter is same for all image regions of an image under consideration. For obtaining the estimates of this parameters we utilize the EM algorithm.

$$\text{Where } t_k(z_s;\theta^{(l)}) = P(k \mid z_j;\theta^{(l)}) = \frac{\alpha_i^{(l)} f_i(z_s,\theta^{(l)})}{h(z_j,\theta^{(l)})}$$

The expected value of $L(\theta)$ is following the heuristic arguments of Jeff A. Bilmes (1998),

$$Q(\theta,\theta^{(i)}) = \sum_{i=1}^{N}\sum_{J=1}^{K}\left[\log(\alpha_j f_i(z_s,\theta^{(i)})\right]t_i(z_s,\theta^{(i)})$$

The update equations of the EM algorithm are

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

$$\mu_k^{(l+1)} = \frac{\sum_{s=1}^{N} t_i(z_s,\theta^{(l)})^{\gamma(N,P)} z_s}{\sum_{s=1}^{N} t_i(z_s,\theta^{(l)})^{\gamma(N,P)}} \text{ and} \tag{8}$$

$$\sigma_i^{(l+1)} = \left[\frac{\sum_{i=1}^{N} t_i(z_s,\theta^{(l)})\left(\frac{\Gamma(3/P)}{P\Gamma(1/P)}\right)\left|z_i-\mu_i^{(l)}\right|^{\frac{1}{P}}}{\sum_{i=1}^{N} t_i(z_s,\theta^{(l)})}\right]^{\frac{1}{P}} \tag{9}$$

5. INITIALIZATION OF PARAMETERS

The efficiency of the EM algorithm in estimating the parameters is heavily dependent on the number of Segments (Clusters (‘K’)) and the initial estimates of the model parameters μ_i, σ_i and α_i (i = 1,—K). Usually in EM algorithm the mixing parameter α_i and the region parameters μ_i, σ_i are known as prior. A commonly used method in initialization is by drawing a random sample in the entire image data (mixture data) (Mclanchan and T. Krishnan (1997), G. Mclanchan and D. Peel (2000)). This method can be performed well when the sample size is large, but the computation time is also heavily increased, when the sample size is small it is likely that some small regions may not be sampled. To overcome this problem, we use Hierarchical clustering algorithm. The number of mixture components is initially taken for Hierarchical clustering algorithm by the histogram of the pixel intensities of the entire image. After determining the final value of the K (number of regions), we obtain the initial estimates the parameters p μ_i, σ_i and α_i for the ith region using the segmented region pixel intensities with the method given by J. Armando *et al.* (2003).

6. SEGMENTATION ALGORITHM

After refining the parameters the prime step is image reconstruction by allocating the pixels to the segments. This operation is performed by Segmentation Algorithm. The image segmentation algorithm consists of 3 steps.

Step 1: obtain the initial estimates of the Finite Generalized Gaussian Mixture Model in each region using the method given by J. Armando *et al.* (2003) and $\alpha_i = 1/K$

Step 2: with the initial estimates obtained in step1, the EM algorithm is iteratively carried with the update equations. The EM algorithm converges when the difference of the old estimates and the new estimates are less than the threshold value (0.001), and the final estimates of the Finite Generalized Gaussian Mixture Model are obtained. The EM algorithm contributes to the segmentation algorithm by improving the parameters of the model.

Step 3: the image segmentation is carried out by assigning each pixel into a proper region (segment) according to the Maximum likelihood Estimate of the jth element L_j according to the following equation

$$L_i = \max_i \left\{ \frac{\exp^{\left|\frac{z_i - \hat{\mu}_i}{A(P_i, \hat{\sigma}_i)}\right|^{P_i}}}{2\Gamma(1+\frac{1}{P_i})A(P_i, \sigma_i)} \right\} \quad (10)$$

where Z_i are the input data (pixel intensities) and $\hat{\mu}_i, \hat{\sigma}_i$ are the estimated parameters respectively.

7. EXPERIMENTAL RESULTS

In order to evaluate the developed segmentation model, consider the image segmentation algorithm with Finite Generalized Gaussian Mixture Model with Hierarchical clustering and apply it to 6 images namely, WOMEN, SUNSET, MAN, LOTUS. HILLS and BULL. We assume that the pixel intensities in each segment of the image follow a Generalized Gaussian Distribution and intensities in each image follows a Finite Generalized Gaussian Mixture Distribution. Using the Pixel grabber under JAVA environment the pixel intensities of the image are obtained. The histograms of the pixel intensities of each are constructed and given in Figure 2.

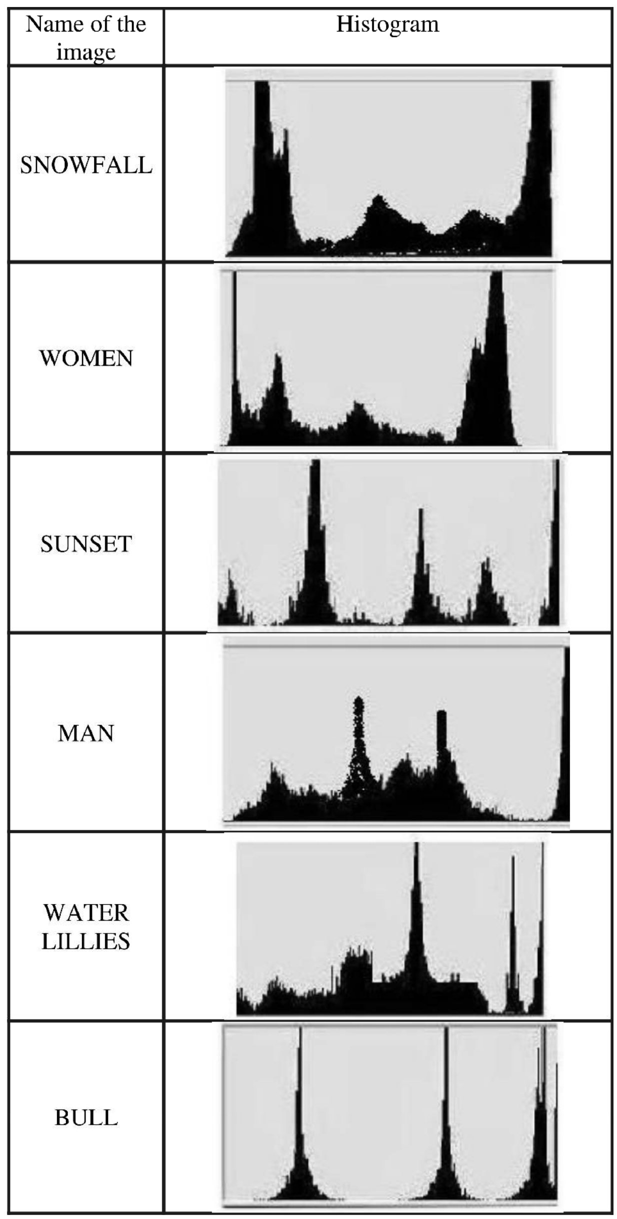


Figure 2: Histograms of the Images

It is observed that each image is a mixture of several image regions, since the histogram of each image is multi model depicting several peaks. The Hierarchical algorithm is performed with pixel intensities of each image and the estimated value of 'K' for each image data is obtained and shown in Table 1.

Table1
Estimated value of K (By Hierarchical Clustering Algorithm)

Image	*Bull*	*Women*	*Sunset*	*Lotus*	*Hills*	*Man*
Estimate of K	3	4	5	5	4	5

From Table 1, we observe that for the images WOMEN and HILLS, are having FOUR regions each, and the images SUNSET, LOTUS and MAN are having FIVE regions each and the image BULL has THREE regions.

The initial values of the model parameters *Pi*, μ_i, σ_i, α_i for i = 1, 2,..K for each image region of the images is computed by using the method proposed by Armando. J *et al.* (2003). Using these initial estimates, the EM algorithm is performed for refining the estimates of the model parameters for each image data. The computed values of the initial estimates and the final estimates of the model parameters K, μ_i, σ_i, α_i for i = 1,2..k for each image are shown in Tables 2a, 2b, 2c, 2d, 2e and 2f.

Table 2a
SUNSET IMAGE (Number of Image Regions = 5)

	Estimation of Final Parameters by EM Algorithm				
	P=0.5	*P=0.6*	*P=0.7*	*P=0.72*	*P=0.75*
Region Weights α_i	0.1132 (0.1310)	0.3216 (0.1321)	0.4220 (0.441)	0.1103 (0.1177)	0.0444 (0.20)
Region Means μ_i	3112.22 (3346.27)	3121.02 (5674.30)	-3112.12 (3412.234)	3112.2 (0.3421)	3123.1 (3111)
Region Variances σ_i	10210.1 (10001.7)	10112.15 (10879.37)	3212.2 (34272.73)	98862.1 (2314.1)	12121.2 (1028.1)

Note: Values in the parenthesis indicate the initial estimates

Table 2b
BULL IMAGE (Number of Image Regions/Segments 'K' = 3)

	Estimation of Final Parameters by EM Algorithm		
	P=0.5	*P=0.6*	*P=0.7*
Region Weights α_i	0.2136 (0.2139)	0.4220 (41150)	0.3644 (0.36950)
Region Means μ_i	3216.21 (1121.21)	-2114.32 (-3124.32)	-3412.211 (1612.23)
Region Variances σ_i	3253.71 (3221.71)	31219.37 (31129.37)	34212.73 (32272.73)

Table 2c
MAN IMAGE (Number of Image Regions/Segments 'K' = 5)

	Estimation of Final Parameters by EM Algorithm				
	P=0.5	*P=0.6*	*P=0.7*	*P=0.72*	*P=0.75*
Region Weights α_i	0.1217 (0.3323)	0.3113 (0.1137)	0.3212 (0.263)	0.1210 (0.1211)	0.1248 (0.1702)
Region Means μ_i	3221.21 (3325.61)	4212.3 (5421.31)	-2411.2 (3112.21)	2921.2 (3031.2)	2912.1 (3121.2)
Region Variances σ_i	43401.71 (43241.7)	29819.3 (2111.37)	34272 (3111.2.)	21121.7 (21349.2)	344212.1 (0.311)

Table 2d
HILLS IMAGE (Number of Image Regions/Segments 'K' = 4)

	Estimation of Final Parameters by EM Algorithm			
	P=0.5	*P=0.6*	*P=0.7*	*P=0.72*
Region Weights α_i	0.13295 (0.1438)	0.32227 (0.1322)	0.42555 (0.4323)	0.1188 (0.2917)
Region Means μ_i	3216.21 (3113.21)	521232 (5324.37)	3412.234 (3022.234)	22454.2 (3112.1)
Region Variances σ_i	11001.71 (11311.71)	10181.30 (11319.60)	34272.09 (10122.1)	13121.32 (10112.1)

Table 2e
WOMEN IMAGE (Number of Image Regions/Segments 'K' =4)

	Estimation of Final Parameters by EM Algorithm			
	P=0.5	P=0.6	P=0.7	P=0.72
Region Weights α_i	0.2132 0.2524	0.3324 0.2143	0.4323 0.234	0.21221 0.2993
Region Means μ_i	3109.79 3216.21	4312.2 5121.21	3001.43 3212.23	3121.3 3022.1
Region Variances σ_i	20901.71 21241.7	19821.37 22221.37	20972.32 22342.7	20122.7 20092.4

Note: Values in the parenthesis indicate the initial estimates

Table 2f
LOTUS IMAGE (Number of Image Regions/Segments 'K' =5)

	Estimation of Final Parameters by EM Algorithm				
	P=0.5	*P=0.6*	*P=0.7*	*P=0.72*	*P=0.75*
Region Weights α_i	0.1032 0.1098	0.232 0.1143	0.3212 0.345	0.1103 0.3234	0.2333 0.1075
Region Means μ_i	33216.2 3276.21	5232.32 36323.55	3412.23 3322.234	3121.1 3211.7	3211.2 3112.
Region Variances σ_i	132101.71 10100.7	224355. 110133	31232.7 32272.7	13112.1 12117.1	12111.3 12131.2

Note: Values in the parenthesis indicate the initial estimates

Substituting the estimates K, μ_i, σ_i and α_i, in the above equations,we obtained the probability density function of each image.

The original and the reconstructed images Finite Generalized Gaussian Mixture Model with Hierarchical Clustering algorithm is shown in Figures 3.

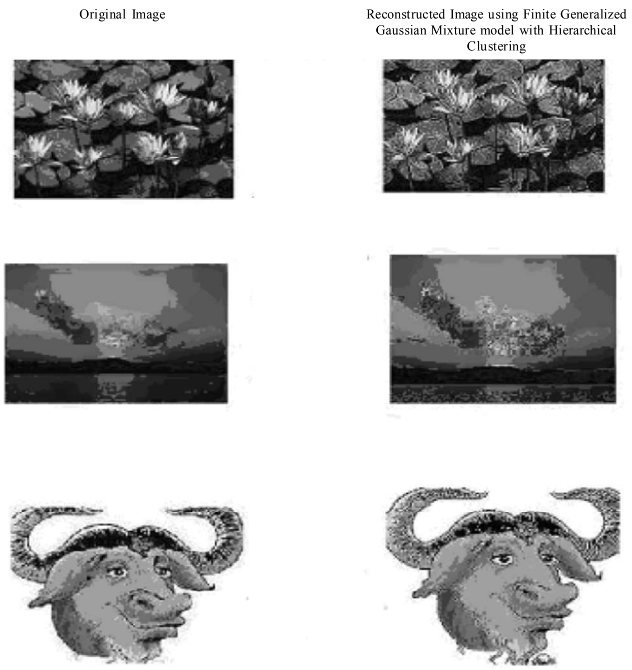
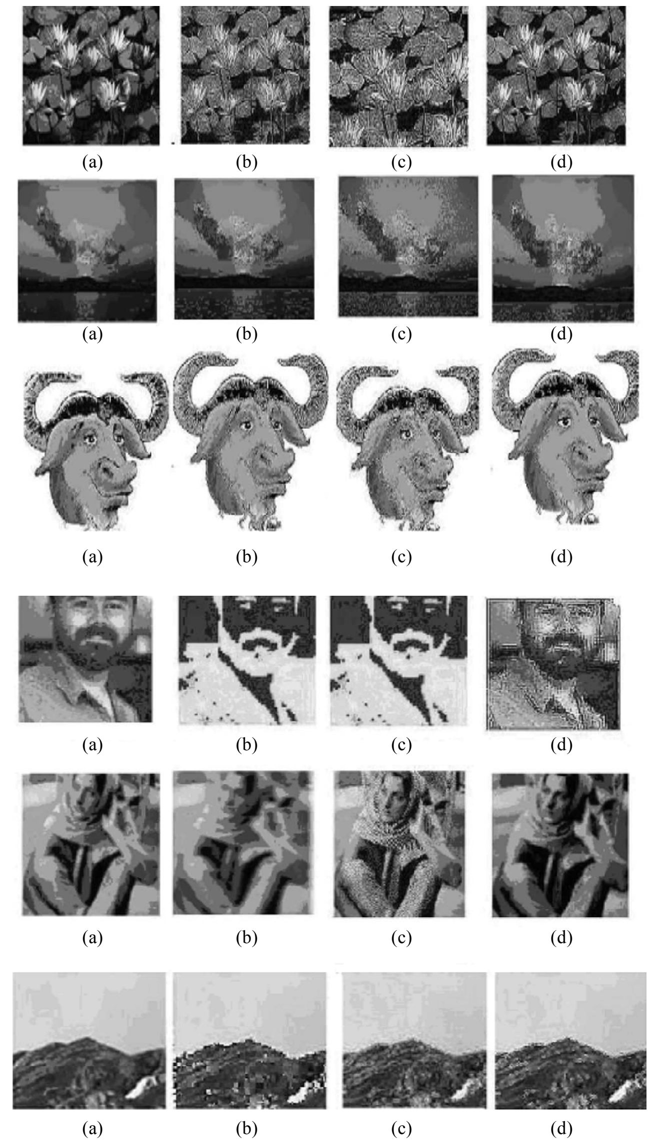


Figure 3

8. PERFORMANCE EVALUATION

To evaluate the performance of the developed algorithm, six images namely WOMEN, SUNSET, MAN, LOTUS HILLS and BULL are considered and compared with the other model based segmentation algorithms, by obtaining their image quality metrics. The Comparisons with other methods like mean shift clustering and graph based segmentation methods are not considered since the interest of the present study is with respect the assumption regarding the pixel intensities being distributed as a mixture of Finite Generalized Gaussian Distribution. The Original and the reconstructed Images of WOMEN, SUNSET, MAN, LOTUS .HILLS and BULL by using the developed image Segmentation algorithm and the earlier existing image segmentation algorithms namely Finite Gaussian Mixture model with Hierarchical Clustering, Finite Doubly truncated Gaussian Mixture Model with Hierarchical Clustering are shown in Figure 4.

After developing the Image Segmentation algorithm it is needed to verify the performance of the algorithm by using Image Quality Metrics such as Average Distance, Image Fidelity, Mean Square Error, Structural Symmetry, Cross Correlation, Maximum Difference, N-Cross Correlation, Quality Index, and Structural Content. The results comparative studies are given in Table 3



(a = original image; b=Image generated by Finite Gaussian Mixture model with Hierarchical Clustering; c= image generated by Finite doubly Truncated Gaussian Mixture model with Hierarchical Clustering and d= image generated by Finite Generalized Gaussian Mixture Model with Hierarchical Clustering)

Figure 4

From this Table 3 and Figure 4, it is observed that the developed algorithm performs much superior to existing algorithms with respect to the Image Quality Metrics

The performance of the Image Segmentation algorithm is also studied through classifier accuracy by computing the misclassification rate (J.Han and M. Kamber (2004). The misclassification rates of the different images namely BULL, WOMEN, MAN, LOTUS ,HILLS and SUNSET with reference to the developed segmentation algorithm and the Finite Gaussian Mixture Model with Hierarchical clustering algorithm are computed and given in Table 4

Table 3
Comparative Study of Image Quality Metrics

IMAGE	*Quality Metric*	*Finite Gaussian Mixture Model with K-Means*	*Finite Generalized Gaussian Mixture Model with K-Means*	*Finite Generalized Gaussian Mixture Model using Hierarchical Algorithm*	*Standard Limits*	*Standard Criteria*
BULL	Average Difference	0.6963	0.0863	0.45275	-1 to +1	Closest to 1
	Maximum Distance	0.6708	0.9708	0.2287	-1 to +1	Closest to 1
	Image Fidelity	1.22208	1.008	0.9001	0 to 1	Closest to 1
	Mean Square Error	0.9982	08972	0.7813	0 to ∞	Closest to 0
	PSNR	23.454	32.454	65.759	0 to + ∞	As Big as Possible
	Image Quality Index	-0.1254	0.2354	0.756	-1 to 1	Closest to 1
WOMEN	Average Difference	0.0543	-0.8383	0.91723	-1 to +1	Closest to 1
	Maximum Distance	-0.4508	-0.3222	1.1461	-1 to +1	Closest to 1
	Image Fidelity	1.5408	0.1124	0.678	0 to 1	Closest to 1
	Mean Square Error	0.7682	0.1213	0.8546	0 to ∞	Closest to 0
	PSNR	36.476	35.122	47.737	0 to + ∞	As Big as Possible
	Image Quality Index	-0.6354	1.023	0.5430	-1 to 1	Closest to 1
LOTUS	Average Difference	0.0563	0.4783	0.56322	-1 to +1	Closest to 1
	Maximum Distance	-0.546	-0.142	1.145	-1 to +1	Closest to 1
	Image Fidelity	1.8978	1.2444	0.618	0 to 1	Closest to 1
	Mean Square Error	0.6482	0.1132	0.7058	0 to ∞	Closest to 0
	PSNR	32.454	35.342	49.876	0 to + ∞	As Big as Possible
	Image Quality Index	-0.4354	-0.127	0.918	-1 to 1	Closest to 1
HILLS	Average Difference	0. 775	-0.6878	0.5621	-1 to +1	Closest to 1
	Maximum Distance	-0.9543	-0.5222	1.1768	-1 to +1	Closest to 1
	Image Fidelity	1.17608	0.5345	0.769	0 to 1	Closest to 1
	Mean Square Error	0.4382	0.1132	0.2255	0 to ∞	Closest to 0
	PSNR	22.454	32.322	29.265	0 to + ∞	As Big as Possible
	Image Quality Index	-0.3254	-0.893	1.0010	-1 to 1	Closest to 1
MAN	Average Difference	0.7863	0.3783	0.87817	-1 to +1	Closest to 1
	Maximum Distance	-0.9708	1.3222	0.89467	-1 to +1	Closest to 1
	Image Fidelity	0.989	0.8744	0.748	0 to 1	Closest to 1
	Mean Square Error	0.9982	0.1232	0.1285	0 to ∞	Closest to 0
	PSNR	12.454	29.342	42.436	0 to + ∞	As Big as Possible
	Image Quality Index	-0.2354	-0.023	0.723	-1 to 1	Closest to 1
SUNSET	Average Difference	0.0783	-0.3793	0.43808	-1 to +1	Closest to 1
	Maximum Distance	-0.6708	-0.3452	0.8978	-1 to +1	Closest to 1
	Image Fidelity	1.76208	1.2444	0.4544	0 to 1	Closest to 1
	Mean Square Error	0.8982	0.7432	0.5998	0 to ∞	Closest to 0
	PSNR	24.454	29.342	39.734	0 to + ∞	As Big as Possible
	Image Quality Index	-0.2354	-0.1733	0.980	-1 to 1	Closest to 1

Table 4
Classifier Accuracy

Name of the Image	*Finite Gaussian Mixture Model with Hierarchical Clustering*	*Finite Doubly Truncated Gaussian Mixture model with Hierarchical algorithm*	*Finite Generalized Gaussian Mixture Model with Hierarchical clustering algorithm*
Bull	93.45	94.76	97.78
Women	96.34	97.11	97.98
Man	95.23	96.13	97.81
Lotus	96.02	96.91	97.54
Hills	96.34	97.12	98.17
Sunset	95.12	96.87	98.43

From the Table 4, it is observed that the accuracy of the developed algorithm is superior to that of the Finite Gaussian Mixture Model with Hierarchical Clustering. It is highly desirable to develop an Image Segmentation Algorithm based on Finite Generalized Multivariate Gaussian Mixture Model with Hierarchical Clustering which will serve as a generic algorithm for analyzing and retrieving several Images.

9. CONCLUSIONS

An image segmentation algorithm has been presented to segment the large scale images using Finite Generalized Gaussian Mixture Model with Hierarchical clustering structure. The Finite Mixture of Generalized Gaussian Distributions include Finite mixture of Gaussian distribution and Finite Mixture of Laplace Distribution and several other Lapty and Platy Kurtic Distributions. As a result of this generic nature this algorithm can handle a vide variety of images. An EM algorithm is developed and used for estimating the model parameters. In our experiments it is observed the developed algorithm perform better with respect to the Image Quality Metrics than the other model based segmentation algorithms. The hybridization approach of hierarchical clustering with parametric models has reduced the misclassification rate. This algorithm can be utilized for Image Analysis and Image Retrieval of Color as well as Grey color images which is shown in Figures 3 & 4.

ACKNOWLEDGEMENTS

The authors express their deep sense of gratitude for the editor and the anonymous referees for their valuable comments and suggestions which have improved the quality of the paper to the present level.

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