ISSN:0975-9646



# Content Based Image Retrievals Based on Generalization of GMM

L.Shanthi Raju[1], Kumar Vasantha[2], Y.Srinivas[3]

[1, 2]*Department of CSE,*
*Avanthi Institute of Engg & Tech,*
*Narsipatnam,Visakhapatnam, AP, India*

[3]*Department of IT, GITAM University,*
*Visakhapatnam, AP, India*

***Abstract-*** **Content Based Image Retrieval's play a dominant role in Image Retrieval's based on some features specified within the image. Content Based Image Retrieval's are very much useful in situations like crime detection where the identification of criminal can be done using the contents (Biometric features) of the accused. In this methodology we formulate the features using Generalized Gaussian Mixture Model. K-Means algorithm is utilized to cluster the images basing on criteria. In order to demonstrate the methodology a huge database of images are formulated and the performance of the developed method is measured using metrics like PSNR, MSE. The developed methodology is also tested with the Berkley Images.**

***Keywords-*** **Content Based Image Retrieval, Generalized Gaussian Mixture Model, PSNR, MSE, Feature Extraction.**

## I. INTRODUCTION

Image Processing plays a significant role on the analysis and the processing of an image. To analyze a image, image segmentation is mainly focused. Image segmentation is a process of converting a heterogeneous data into homogeneous data [1]. Image segmentation has many applications such as medical analysis, robotics, car manufacturing and along with the other applications. Content Based Image Retrieval predominantly uses the methodology of image segmentation to segment a Image of interest or region of interest from the selected images based on the criteria. These features can be either texture, color, shape, pattern or any other specific feature that deem fit to retrieve a image or identify a image based on the criteria. Several Content Based Image Retrieval models have been discussed in literature. Most of the techniques highlighted in the literature is either based on feature extraction using PCA, ICA, LDA or MDL. However these methodologies are non-degenerative and generative models like Gaussian Mixture Model are also discussed ([2][3][4][5][6]). Among the generative and degenerative models, generative models are mostly preferred since the retrieval or the identification of the images in these methodologies are carried out using the parameters specify within the particular images. Moreover parametric models are more advantageous than non parametric models [ S.K Pal, N.R Pal (1993)]. With this as the back drop Content Based Image Retrieval based on Gaussian Mixture Model are also presented in recent [7][8][9]. However the main disadvantage of using Gaussian Mixture Model is that , it assumes the images always to be symmetric in shape and the range is considered to be infinite, but in reality images are not always symmetric in shape and does not always posses infinite range. Hence to overcome these disadvantages in this paper a novel methodology using Generalized Gaussian Mixture Model is presented to retrieve the images. The rest of the paper is organized as follows section 2 of the paper presents the Generalized Gaussian Mixture Model, in section 3 K-Means algorithm is presented, section 4 briefly discusses the methodology and section 5 of the paper deals with the experimentation. The evaluation is carried out by using quality metrics and the results are presented together with conclusion in section 6.

## II. GENERALIZED GAUSSIAN MIXTURE MODEL

Generalized Gaussian Mixture Model is utilized in [21] for segmenting the images. It includes the Gaussian Mixture Model as a particular case. The PDF of the Generalized Gaussian Mixture Model is given by

$$f(x)=\frac{1}{\sqrt{2\pi\sigma}}e^{-\left(\frac{p*x(i,j)*\bar{x}(i,j)}{2\sigma^2}\right)}+p*\sum_{\substack{0\le i\le m\\0<j<n}}\left[\frac{x(i,j)*\bar{x}(i,j)}{2\sigma}\right]$$

The generalized Gaussian Mixture Model is preferred since it caters the images which are both symmetric and asymmetric in nature

## III. K-MEANS ALGORITHM

K-Means algorithm is utilized in this paper for effective clustering. In order to segment the unsupervised image, K-Means algorithm will be best suitable. In K-Means algorithm the main difficulty is the initialization of $k$ [1, 3] for which we have used the histogram and based on the peaks the initial value of $k$ is assumed and the K-Means algorithm is performed. Since the value of $k$ is initialized it is totally pseudo supervised learning mechanism. The K-Means algorithm is given below.

Step 1: Begin with the initial value of $k$.
Step 2: Select number of clusters.

Step 3: Partition the input pixels into $k$ clusters by assigning each pixel $x_i$ to the closest centroid $v$ using any of the distance measure.

Step 4: Compute the cluster assignment metrics using

$$\sum_{i=1}^{k} u_{ij} = 1 \; \forall \, i \,\&\, j$$

Where $u$ is the cluster assignment matrix.

Step 5: If the cluster centroid or assigned matrix changes, repeat the above steps.

## IV. METHODOLOGY

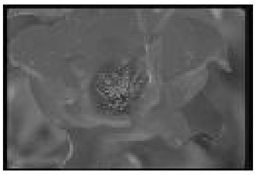
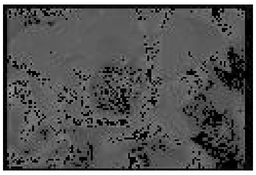
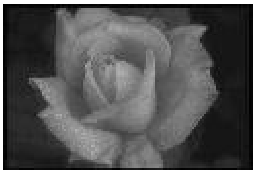
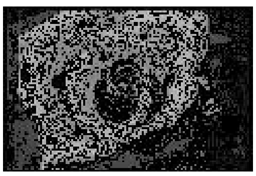
In order to segment the image, the pixels from input image are to be extracted. Apply the K-Means algorithm give in section 3 to find the clusters inside the image region. Apply the PDF of Generalized Gaussian Mixture Model by varying different values of $k$ & $c$ (location and scale parameters). After identifying the PDF of each segment using Generalized Gaussian Mixture Model, the process of segmentation is done by using the component likelihood function. The images are retrieved by using the features; in this method we calculate the features vectors (μ and σ) for each of the images. The image retrieval is done based on the features μ and σ. In order to evaluate the methodology we have considered a database of hundred images for testing purpose. For each of these images the feature vectors are calculated. The preprocessing is performed on the images and the clustering is performed to convert the heterogeneous data into homogeneous data. In order to retrieve the images, we have calculated the parameters μ and σ for each of the clustered images theses features are used as feature vector to extract the images of relevance, we use this values of The experimentation conducted is presented in section 5.

## V. EXPERIMENTATION

In order to develop the segmentation model proposed, we have used the VB.NET platform by considering Berkley images of size 128 x 85. We have considered fourteen images of similar shape but differing in colors and the images which are unique as a trial basis, all from Berkley image dataset of fixed size and considered color images for conducting the model.

The color images are converted to gray scale images and the methodology proposed in section 4 is performed. The various images considered under study are Roses, Ships, Car and Dog. The outputs generated are shows in Fig.1.

Fig.1. Outputs Generated using Methodology

| S/No | Color Image | Grayscale Image | Segmented Image | Parameters |
|---|---|---|---|---|
| 1 |  |  |  | **μ = 25.3608203865643** <br> **σ = 0.0584613911197611** |
| 2 |  |  |  | **μ = 74.6130514705882** <br> **σ = 0.198261524000891** |
| 3 |  |  |  | **μ = 90.4266544117647** <br> **σ = 0.135497805861917** |
| 4 |  |  |  | **μ = 112.481158088235** <br> **σ = 0.27295656947286** |

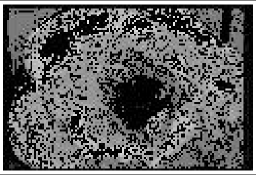
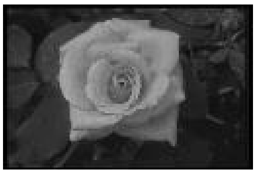
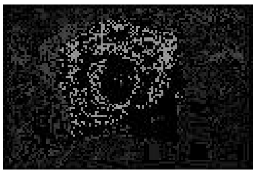
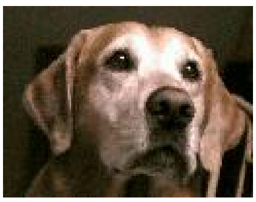
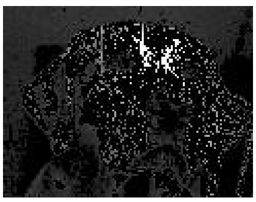
| S/No | Color Image | Grayscale Image | Segmented Image | Parameters |
|---|---|---|---|---|
| 5 |  |  |  | μ = 105.063878676471<br>σ = 0.133785333689716 |
| 6 |  |  |  | μ = 140.945036764706<br>σ = 0.26003952824247 |
| 7 |  |  |  | μ = 63.9956801470588<br>σ = 0.20334513878818 |
| 8 |  |  |  | μ = 121.2607421875<br>σ = 0.130362461553884 |
| 9 |  |  |  | μ = 92.6241861979167<br>σ = 0.0536301301046354 |
| 10 |  |  |  | μ = 76.7738444010417<br>σ = 0.199690358596313 |
| 11 |  |  |  | μ = 108.857904411765<br>σ = 0.36628303349559 |
| 12 |  |  |  | μ = 76.6148756377551<br>σ = 0.302197657512174 |

Fig.1. Outputs Generated using Methodology

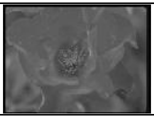
| S/No | Parameters | Image Retrieved |
|---|---|---|
| 1 | μ = 25.3608203865643<br>σ = 0.0584613911197611 |  |
| 2 | μ = 74.6130514705882<br>σ = 0.198261524000891 |  |
| 3 | μ = 90.4266544117647<br>σ = 0.135497805861917 |  |
| 4 | μ = 112.481158088235<br>σ = 0.27295656947286 |  |
| 5 | μ = 105.063878676471<br>σ = 0.133785333689716 |  |
| 6 | μ = 140.945036764706<br>σ = 0.26003952824247 |  |
| 7 | μ = 63.9956801470588<br>σ = 0.20334513878818 |  |
| 8 | μ = 121.2607421875<br>σ = 0.130362461553884 |  |
| 9 | μ = 92.6241861979167<br>σ = 0.0536301301046354 |  |
| 10 | μ = 76.7738444010417<br>σ = 0.199690358596313 |  |
| 11 | μ = 108.857904411765<br>σ = 0.36628303349559 |  |
| 12 | μ = 76.6148756377551<br>σ = 0.30219765751214 |  |

Fig.2. Image Retrieved Based on Content μ and **σ**

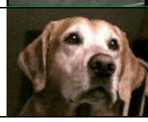
The images after segmenting are reconstructed using the heuristics of random number generator and assigning each pixel into its proper location.

## VI. Image Quality Metrics

In order to evaluate the model Image Quality Metrics proposed by ESKIVIGLOS [11] and we have used PSNR, MSE and Image Fidelity for evaluating our model. The formulae for calculating these quality metrics are given below.

| Image Metric | Formula | Standard limits | Best |
|---|---|---|---|
| PSNR | $10*\log10(255/\sqrt{MSE})$ | (-∞, +∞) | If tends to +∞ |
| MSE | $\frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{N}[z(i,j)-\hat{z}(i,j)]^2$ | (0, 1) | As closer to 0 |

The images Roses, Ships, Car, and Dog are evaluated using these metrics and the results obtained are shown in Table 1.

| S/No | Color Image | Metric | Obtained value using GMD |
|---|---|---|---|
| 1 |  | MSE | 0.168198529411765 |
| | | PSNR | 27.9362908324982 |
| 2 |  | MSE | 0.479411764705882 |
| | | PSNR | 25.661858367531 |
| 3 |  | MSE | 0.435202205882353 |
| | | PSNR | 25.8719463644539 |
| 4 |  | MSE | 0.525183823529412 |
| | | PSNR | 25.4638451009167 |
| 5 |  | MSE | 0.409283088235294 |
| | | PSNR | 26.0052828054942 |
| 6 |  | MSE | 0.420496323529412 |
| | | PSNR | 25.946590789138 |
| 7 |  | MSE | 0.576286764705882 |
| | | PSNR | 25.2622085769968 |
| 8 |  | MSE | 0.560791015625 |
| | | PSNR | 25.3213965682033 |
| 9 |  | MSE | 0.463948567708333 |
| | | PSNR | 25.7330526127561 |
| 10 |  | MSE | 0.480061848958333 |
| | | PSNR | 25.658915836931 |
| 11 |  | MSE | 0.487591911764706 |
| | | PSNR | 25.6251193399636 |
| 12 |  | MSE | 0.550701530612245 |
| | | PSNR | 25.3608203865643 |

The values obtained from the image using the developed models are compared to that of existing model based on Gaussian Mixture Model and is presented in table 1.

## VII. CONCLUSIONS

In this paper we have developed and analyzed a model based on Generalized Gaussian Mixture Model. The images considered for study are from benchmark image dataset, Berkley and we have considered five images namely Roses, Ships, Car and Dog. The outputs obtained by the developed method are tested using Image Quality Metrics from the above metrics. It can be clearly seen that the developed model out performs the existing models. The developed model will be well suited to those set of images where the shape of image frequency curve is asymmetric.

## VIII. REFERENCES


[1] Y. Srinivas et al, "An Efficient Approach for Medical Image Segmentation Based on Truncated Skew Gaussian Mixture Model using K-Means Algorithm", International Journal of Computer Science and Telecommunications, pp 79-86, Aug 2011.

[2] X. Zhou and T. Huang, "Relevance Feedback For Image Retrieval: A comprehensive review," ACM Multimedia Syst. J., vol. 8, no. 6, pp. 536–544,Apr. 2003.

[3] Y. Chen, X.-S. Zhou, and T.-S. Huang, "One-class SVM for learning in image retrieval," in Proc. IEEE ICIP, 2001, pp. 815–818.

[4] P. Hong, Q. Tian, and T. S. Huang, "Incorporate support vector machines to content-based image retrieval with relevant feedback," in Proc. IEEE ICIP, Vancouver, BC, Canada, 2000, pp. 750–753.

[5] D. Tao, X. Li, and S. Maybank, "Negative samples analysis in relevance feedback," IEEE Trans. Knowl. Data Eng., vol. 19, no. 4, pp. 568–580,Apr. 2007.

[6] W. Bian and D. Tao, "Biased discriminant Euclidean embedding for content-based image retrieval," IEEE Trans. Image Process., vol. 19,no. 2, pp. 545–554, Feb. 2010.

[7] M. R. Azimi-Sadjadi, J. Salazar, and S. Srinivasan, "An adaptable image retrieval system with relevance feedback using kernel machines and selective sampling," IEEE Trans. Image Process., vol. 18, no. 7, pp. 1645–1658, Jul. 2009.

[8] X. Zhou and T. Huang, "Small sample learning during multimedia retrieval using biasmap," in Proc. IEEE Int. Conf. Comput. Vis. PatternRecog., 2001, pp. 11–17.

[9] S. T. Roweis and L. K. Saul, "Nonlinear dimensionality reduction by locally linear embedding," Science, vol. 290, no. 22, pp. 2323–2326, Dec. 2000.

[10] J. Yu, Q. Tian, T. Rui, and T. S. Huang, "Integrating Discriminant and descriptive information for dimension reduction and classification," IEEE Trans. Circuits Syst. Video Technol., vol. 17, no. 3, pp. 372–377, Mar. 2007.

[11] X. Li, S. Lin, S. Yan, and D. Xu, "Discriminant locally linear embedding with high-order tensor data," IEEE Trans. Syst., Man, Cybern. B, Cybern.,vol. 38, no. 2, pp. 342–352, Apr. 2008.

[12] M. Sugiyama, "Dimensionality reduction of multimodal labeled data by local Fisher discriminant analysis," J. Mach. Learn. Res., vol. 8, pp. 1027–1061, 2007.

[13] X. He and P. Niyogi, "Locality preserving projections," in Proc. Adv. Neural Inf. Process. Syst., 2004, vol. 16, pp. 153–160.

[14] X. He, S. Yan, Y. Hu, P. Niyogi, and H. Zhang, "Face recognition usingLaplacian faces," IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 3,pp. 1624–1637, Dec. 2005.

[15] K. Lu and X. He, "Image retrieval based on incremental subspace learning," Pattern Recognit., vol. 38, no. 11, pp. 2047–2054, Nov. 2005.

[16] J. Chen, S. Shan, G. Zhao, X. Chen, W. Gao, and M. Pietikainen, "WLD: A robust descriptor based on Weber's law," IEEE Trans. Pattern Anal.Mach. Intell., vol. 32, no. 9, pp. 1705–1720, Sep. 2010.

[17] H. Wang, "Nearest neighbors by neighborhood counting," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 6, pp. 942–953, Jun. 2006

[18] S. C. Hoi, W. Liu, M. Lyu, and W. Ma, "Learning distance metrics with contextual constraints for image retrieval," in Proc. Comput. Vis. Pattern Recog., 2006, pp. 2072–2078.

[19] Y. Liu, D. Xu, I. W. Tsang, and J. Luo, "Textual query of personal photos facilitated by large-scale Web data," IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 5, pp. 1022–1036, May 2011.

[20] J. Yang, K. Yu, F. Lv, and T. S. Huang, "Supervised translationinvariant sparse coding," in Proc. Comput. Vis. Pattern Recog., 2010, pp. 3517–3524.

[21] Srinivas Yarramalle, et al "Unsupervised Image Segmentation using Finite Doubly Truncated Gaussian Mixture Model and Hierarchical Clustering. Current Science, 71-84, Aug 2007.

[22] S. K. Paul, N. R. Paul, "Review of Image Segmentation Techniques, IEEE transactions on image processing, 1993.