Towards effective Content Based Image Retrieval based on Local Binary Patterns and Finite Beta Mixture Model

Subash Chandra Chadalavada, Srinivas Yarramalle

Abstract: Content Based Retrievals has major role in many practical situations where the images are to be extracted based on the content. However, with the vast dimensionality of the data surrounding retrieval of the relevant information in minimum instance of time together with accuracy is a challenging task. This article presents an ideology to counter attack the challenge by proposing a model based on Finite Beta Mixture Distribution. In order to extract the Features, Local Binary Patterns (LBP) are considered and the proposed work is implemented based on Flickr Dataset

Index Terms: CBIR, LBP, Dimensionality, Beta Mixture Model, Flickr.

I. INTRODUCTION

Content Based Image Retrieval has significant importance while retrieving the data of interest from voluminous available sources. With the technological improvements, the data available has scaled up both in volume and breadth. Therefore, a huge repository of data is pooled and is available for access across the globe. This data majorly contains the information in unstructured format and effective methodologies are to be developed to overcome the challenges with regard to mining from these unstructured documents. Many models have bee proposed by researchers in this field of work and most of the works are based on Artificial Intelligence, Optimization Techniques, Graph Cut Methods together with models based on Gaussian Mixture Model and Gamma Mixture Models. However, these models are effective when the data is small in dimensionality and also if the data is free from the raw collection of data. Since, the methodologies based on statistical modeling are assumed to be most sophisticated than the degenerative models, effective techniques are therefore emerged by considering modeling approaches with statistical distribution.The frontier among these models is considered to the Gamma Mixture Models and it is considered because of the fact that the basic assumption of the fact that the basic assumption of the images in general attribute a wide spectrum which is mostly normal in shape. With this assumption, Gaussian Distribution has become the primary consideration. However, the main curse of Gaussian Mixture Model is its dimensionality which takes the infinite range from $-\infty$ to $+\infty$ and with this assumption the methodologies are developed for retrievals based on the content.

In particular, any image information will be of finite range and hence when Gaussian Mixture Model is considered for retrievals, results improve. But, by doing so, either retrieving the images with maximum time limit or the retrieval accuracy may be at stake. Also the GMM methodologies don't consider the relationships between the adjacent pixels while formulating the model. In CBIR, the effective retrievals can be subjected to the identification of the image data based on the consideration of the neighborhood pixels. Therefore, to meet the challenges, the GMM fails and hence methodologies are considered based on Gamma Distribution.

Gamma Mixture Models are well suited for processing the speech signals which are mostly asymmetric and in contrast, the images globally available are not always asymmetric. Therefore, with this limitation of Gamma Mixture Model, methodologies need to be proposed for effective retrievals of images from the huge repositories.

In this direction, the present article proposes a model based on Finite Beta Mixture Model. The main advantage of this model is that it assures that the image is finite in nature and estimates densities based on the neighborhood dependencies. In this preset article, to showcase the effective retrievals a database from Flickr is considered. For any effective retrievals, Feature Vectors play a significant role. In this article, the LBPs are considered for the retrieval of the features. The rest of the article is articulated as follows.

Section 2 presents an insight on the Finite Beta Mixture Model and in Section 3 the Dataset considered is proposed. The Feature Extraction method based on LBP is presented in Section 4 and to derive the efficiency of the model the quality metrics are considered and are presented in Section 5. The experimental results together with results derived are highlighted in Section 6 the concluding Section 7 summarizes the article.

II. FINITE BETA MIXTURE MODEL

In medical imaging, technologies like MRIs exhibit denser correlation coefficients. These coefficients are computed at several levels to enable us to identify the disease.

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The Beta Mixture Models generally are used for identification of relationships between these coefficients. So, in cases where we need to correlate the coefficients for identification of shapes, Beta Mixture Models are well suited and thus Finite Beta Mixture Modal is finalized to be used in the present article.

The Beta Mixture Model uses a vector for correlation of coefficients, these coefficients are supposed to produce different probability distributions, which in our case, is the Beta distribution.

The Beta distribution is modeled with each pixel in the image ‘ x_i ‘ is considered and is subjected to a linear transformation

$$y_{i=}\left(\frac{x_i+1}{2}\right)$$

- - - (1)

This is the only to ensure that the range of the image pixels studied are normalized between the range of 0 to 1. The index ‘ i ‘ represent the image pixel with respect to the correlation coefficient ‘ y ‘.

Let y_i , i = 1 to N denote the correlation coefficients of the pixels which are transformed into vector for all the total number of pixels inside the image regions.

In order to compute the mixture of all components, the PDF of the Beta Mixture Model is considered and is presented by using the equation (2) as follows

$$B(x_i,\alpha_i,\beta_i) = \sum_{i=1}^{L}\prod_i f_i(\mu_i|\alpha_i,\beta_i)$$

- - - (2)

III. IMAGE SIMILARITY

The query image is considered and the probability density function of the query image is extracted using the Finite Beta Mixing Model (FBMM). The relevance of the probability density functions is obtained using the KL divergence. The images that were mapped relatively are retrieved based on the KL value. The formula to calculate the divergence of KL is given below.

$$KL(p_1,p_2)=\int p_1(x)\log\left(\frac{p_1(x)}{p_2(x)}\right)dx$$

---(3)

Where ‘p1’, ‘p2’ are the two Probability Density Functions worked out on diverse images, formulated using Finite Beta Mixture model.

IV DATASET CONSIDERED

For this model, the Flickr Dataset, web-based social network image database consisting of contributions from its online users is considered. Flickr currently has 87 million regular users and is having a collection of more than 3.5 million images. The collection includes, images and descriptions in several languages ranging from English, Chinese, French, German, Hindi, Korean, etc. It also houses several images ranging from Nature, Birds, Animals, Logos, Balloons, Shapes, Plants, etc. Each image is normalized. This data set consists of both color and grayscale images

Figure-1 Flickr dataset.

V. FEATURE EXTRACTION BASED ON LBP

LBPs are taken for feature extraction of image in this article. This is done by identifying the value of a core pixel by taking into account the number of pixels surrounding it. The value for which is to be assigned as a middle value in a 3x3 window that is formulated by extracting the sub-window as per the user’s defined feature. This center pixel is considered and the value is to be assigned to that pixel. In this case, the value of the center pixel is based on its adjacent pixels. Each pixel around the neighbor is considered and if the neighbor pixel is greater than the core pixel its vale is assigned to 1 else to 0. The value for each such core is identified using a clockwise rotation. This is explained with a 3x3 matrix considered below.

$$\begin{bmatrix} 1 & 8 & 2 \\ 4 & 9 & 11 \\ 10 & 1 & 7 \end{bmatrix}$$

Now, the core pixel = 9

To find LBP,

Consider every pixel within the neighbors of 9 and if the value of pixel > 9 assign ‘1’ else assign ‘0’.

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & C & 1 \\ 1 & 0 & 0 \end{bmatrix}$$

Now the code is generated in an anti-clock wise manner as, 10 0 0 0 1 0 0

And its binary equivalent is 132.

This 132 value is considered as the core for the center pixel. These features are considered for effective retrievals.

In order to present with proposed model, the images in the dataset are considered and are given as inputs to the model based on FBMM.

In this model, each of the input images is considered and are given as inputs to the FBMM given in equation. (3) and the probability density function are acquired. The probability density function of the query image is extracted using FBMM.

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The query image is considered and using the LBP the relevant images in the database are identified. Now, the PDF of the Query images are mapped to those of the images retrieved against the histograms of the LBP. The relevance of the probability density functions is obtained using KL divergence. The images which relatively mapped are retrieved basing on KL value.

VI. EFFICIENCY AND QUALITY METRICS

In order to appraise the performance of the projected method, assessment metrics such as Precision and Recall are considered. The formulas for computing are given below.

a) Precision

It is the ratio of the number of correct images retrieved against that of the total number of not associated and associated images retrieved. It is generally articulated in terms of percentage.
Precision = (A / (A + C))* 100;
A: Number of related images retrieved.
C: Number of irrelevant images retrieved.
A + C: Total number of irrelevant + relevant images retrieved

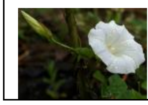
b) Recall

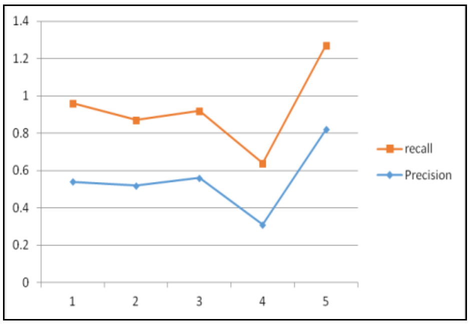
It is the ratio of the number of relevant images retrieved to the total number of relevant images in the database. It is usually expressed as a percentage.
Recall = (A / (A + B)) * 100
A: Number of relevant images retrieved
B: Number of relevant images not retrieved
A + B: The total number of relevant images

VII EXPERIMENTAL RESULTS

The pixels of the images are considered and the relevant values of the pdf are identified using Finite Beta Mixture Model, for each of these segmented images, the PDF values obtained are stored and the retrieval is based purely on the comparison of similarity values. The PDFs of the relevant images which are mapped are considered and for those images, to identify the similarity, the LBP metric presented in section 3 is considered. The corresponding output is completed for obtaining the relevancy.
The relevancy of the retrievals based on the PDF is evaluated using the metrics; Precision and Recall and the results obtained are presented in the Table 2

Table 1: Images retrieved based on PDF values

Input	Grey scale images	PDF Values	
		Min	Max
		0	21
		0	14
		0	32
		0	39
		0	36
		0	39



Graph 1: Graph Representing precision and recall

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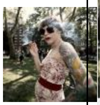
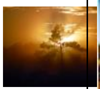
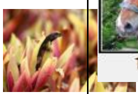
Input	Images retrieved based on PDF Values	No of relevant images	Precision	recall
		1	0.54	0.42
		2	0.52	0.35
		2	0.56	0.36
		1	0.31	0.33
		2	0.82	0.45
		1	0.67	0.37

Table 2: For the given query image the images retrieved based on PDF Values

VIII. CONCLUSION

In this article a methodology based on image retrievals is presented using the methodologies based on FBMM on Flickr Dataset and the results obtained are presented in Tables 1 & 2. The results derived showcase that the derived methodology is adhering to the ranges of the similarity measures which show case the effectiveness of the model.

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