Indian Journal of Science and Technology, Vol 9(46), DOI: 10.17485/ijst/2016/v9i46/91831, December 2016
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Hybrid Classifier based Content based Image Retrieval

P. Vijayakumar , R. Abhishek and Kundala Sandeep

ECE Department, SRM University, Chennai – 600001, Tamil Nadu, India;
vijay_at23@rediffmail.com, abhishekramesh96@gmail.com, sandeepkundala@gmail.com

Abstract:

Objectives: Nowadays, the capacity of digital image information is rapidly surging. The computational complexity of retrieving images from database also increases. **Methods/Statistical Analysis**: Texture and colour are the most important components of visual information which can be used effectively to reduce the complexity. This paper presents Content-Based Image Retrieval System (CBIR) based on texture and colour similarity. The RGB colour space and the colour histogram are used as the colour feature of each image. The texture of each image is obtained by applying gray level co-occurrence matrix. **Findings:** Based on the similarity between image features CBIR methods retrieve images accurately from the image database. But the traditional system will work well only for the data set which has more dissimilarity. In this study, based on combining the Gaussian Mixture Model(GMM) with k-means clustering algorithm, a new hybrid algorithm for clustering is proposed. A one to one matching scheme is used to compare the query and target image on the basis of all the features extracted. This hybrid Gaussian mixture model will provide more accurate retrieval in the case of the dissimilarity between the image data set is very low. The proposed system is capable of working fewer dissimilarity data set as well more dissimilarity data. **Applications/Improvements:** The proposed hybrid retrieval method provide more accurate retrieval with the precision measures of 98% and also more robustness with retrieval of 95%.

Keywords: Content-Based Image Retrieval (CBIR), Co-occurrence Matrix, Expectation-Maximization (EM) Algorithm, Feature Extraction, Gaussian Mixture Model (GMM), K-Means Clustering Algorithm

1. Introduction

In the digital era, we use images for every human activity, such as academics, government, libraries, security, hospitals, and so on. Image database system contains a large collection of image data[1]. Image retrieval in the computer system is a feature for retrieving images from an enormous database like WANG[2], MIRFLICKR-25000, ZUBUD, UCID or Microsoft Object Class Recognition.

This paper proposes the techniques for CBIR to overcome the image retrieval problems of annotation-based methods mentioned above. It usage is to explore and recover digital images and was presented to discourse the intricacies associated to the text-based image retrieval. The aim of the CBIR is efficiently indexing the image and retrieving it and reducing the necessity of human interference in the indexing procedure.

In this paper, Gaussian Mixture Models (GMMs) are being represented through images. A region with analogous colour and texture of the image represents each component of the mixture. This method allows images to be represented by the objects found on them. The kind of an object cannot be recognized; nonetheless the representation holds the data. Clustering used to divide the data set into different groups[3]. It helps us to reduce the searching time to retrieve the image.

K mean clustering algorithm is employed for the clustering purpose as it is efficient technique [4,5]. But for some cases where the similarity between data set is more K means fail but GMM would be optimum. So, a hybrid algorithm is used with the combination of GMM and K-mean.

*Author for correspondence

GMM based k-means clustering will help solve the problem of finding the global solution. In the case of highly correlated images this hybrid algorithm will outform[6].

Texture and colour features is used as an efficient feature vector for fast and accurate retrieval[7],[8]. PicSOM is a technique for efficient retrieval presented in few cases.[9,10] by using GMM image matching based on Kullback-Leibler divergence.

2. Texture and Colour Features based Hybrid CBIR System

The algorithm of the CBIR which is used in this work is given in Figure 1.it consist of feature extraction of texture and colour. by using the feature vector the clustering algorithm the image is clustered and retrieved.

2.1. Dataset

Data collection is carried out by collecting image data necessary for the pre-processing. It is then stored in the image database. The WANG database is a subset of images from the Corel stock photo database. In WANG database, the images are divided into ten classes containing 100 images which are widely used for testing and evaluating CBIR systems.

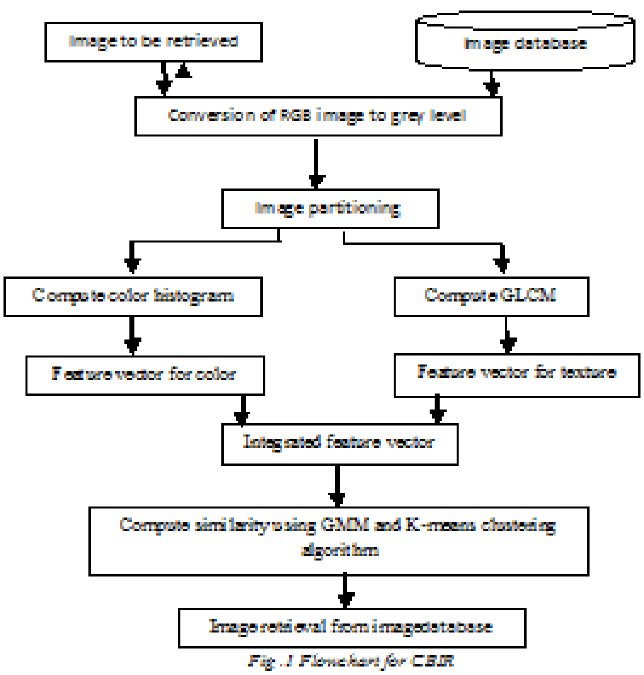

Figure 1. Flowchart for CBIR.

2.2. Feature Selection

In image retrieval systems, as all the features are not needed, feature selection plays a key role for significantly increasing the accuracy[11]. The features like histogram, dominant colours, colour moments and co-occurrence matrix are used as a feature vector

2.2.1. Colour feature extraction

A colour features are computed by means of colour histogram as an efficient approach[12].

$$hc(m) = \frac{1}{XY}\sum_{x=0}^{X-1}\sum_{y=0}^{Y-1} I(x,y) \quad (1)$$

I(x ,y) is input colour image

$$I_h(x,y) = \begin{cases} 1 \ if \ \mathbf{I(x,y) in\ bin\ m,} \\ \mathbf{0} \ otherwise \end{cases} \quad (2)$$

2.2.2. Texture Feature Extraction

The texture is the low-level pictorial arrangements of uniform properties which have on no account to association to unique colour or intensity. Surface arrangement and surrounding environment relationship are the main information which is held by the texture. Hence, the unique physical composition of a surface is described by it. The texture-based technique classifies itself into three primary methods: statistical, spectral, and structural methods.

The alteration in the combination of pixel values has been shown through the Co-occurrence matrix tabulation. Haralick features, include texture properties like contrast, correlation, energy, and homogeneity. Co-occurrence matrix C (i, j) is used to compute the co-occurrence of pixels with gray values i and j at a given distance d that is the polar coordinates (d) with discrete length and orientation. θ takes the values 0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°, respectively.

$$C_{\theta,d}(i,j) = \# \begin{cases} 1, if\ I(x_1,y_1) = i, and\ I(x_1 + d\cos\theta, y_1 + d\sin\theta) = j \\ 0, otherwise \end{cases} \quad (3)$$

Number of elements in the set is being depicted by #, space amongst gray-level value i and j of the image by d, I(i, j)=0-255 depicts the amount of likely graylevels in the image whereas the co-occurrence matrix C (i, j) aspect is M*N.

Image consistency measures such as homogeneity, angular second moment, and consistency are also called as Energy. When gray-level strengths are local to each other, energy value is low. The value of energy is in elevation. When all the matrix elements are amorphous

$$\text{Energy} = \sum_i \sum_j C^2_{\theta,d}(i,j) \tag{4}$$

Opposite of Energy is given by Entropy;

$$\text{Entropy} = -\sum_i \sum_j C_{\theta,d}(i,j) \log C(i,j)\Big|_{\theta,d} \tag{5}$$

Contrast is also known as inertia and processes the variations in the moment of a matrix. If the image has in elevation local variation the value will be up surging.

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 C_{\theta,d}(i,j) \tag{6}$$

Linear reliance of the gray level data in the matrix is calculated by Correlation. no instant conclusion about the image can be inferred by head or low correlation values.

$$\text{Correlation} = \frac{\sum_i \sum_j (ij) C(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{7}$$

Inverse Difference Moment (IDM) is referred as local homogeneity. The matrix elements uncertainty paves the way for tall values of like gray levels which are in neighborhood while the value of the function is in elevation.

$$\text{IDM} = \sum_i \sum_j \frac{C_{\theta,d}(i,j)}{|i-j|^2}, \ i \neq j \tag{8}$$

Where, means μ_x, μ_y and standard deviations σ_x, σ_y are defined as follows:

$$\mu_x = \sum_i i \sum_j C(i,j) \tag{9}$$

$$\mu_y = \sum_j j \sum_i C(i,j) \tag{10}$$

$$\sigma_x = \sum_i (i - \mu_x)^2 \sum_j C(i,j) \tag{11}$$

$$\sigma_y = \sum_j (j - \mu_y)^2 \sum_i C(i,j) \tag{12}$$

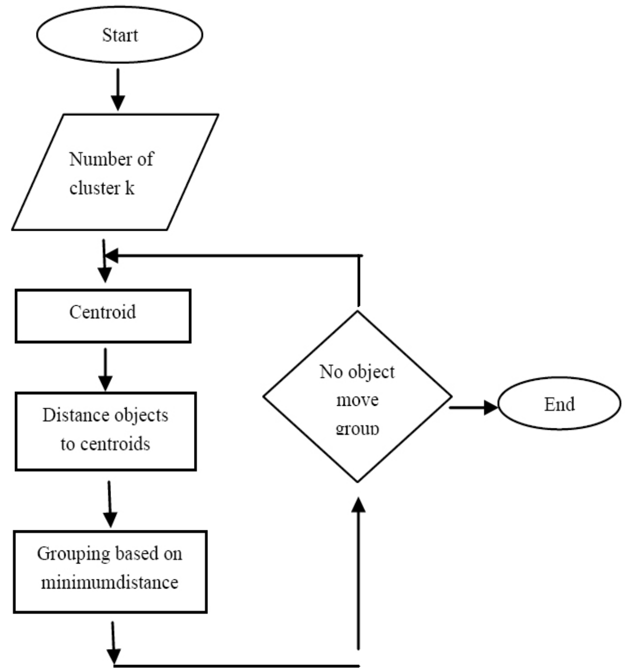

Figure 2. Flowchart for k means clustering.

2.2.3. K-means clustering algorithm

K-means clustering algorithm is implemented due to its efficiency and simplicity. K-means clustering algorithm provides the solution for the mixture of Gaussian problem by performing iterative relocation of the dataset into k clusters to minimize the Within Cluster Sum of Squares (WCSS). The K-means clustering algorithm is given in Figure.2.

2.2.4. Gaussian Mixture Model (GMM)

Gaussian mixture model is one of the density models that contain many Gaussian component functions which are combined with the weight values to generate multi model density .It has a very high flexibility and precision rate as compared to other models[13].

Consider N number of classes labeled by n ∈N ≅{1,….N} related to diverse entities. Consider the neighbourhood of a pixel. With the help of this S×S sub-images, block features can be calculated, and classes are assigned to these blocks [14]. B is used to represent set of blocks. The neighborhood of a block B is considered as patch P(B). It is a collection of blocks in a larger T×T sub-image with B as its center.

2.2.5 Expectation Maximization (EM) Algorithm

solving maximum likelihood problems can be solved through iterative algorithm such as Expectation Maximization. Considering the set of perceived data X, produced by the probability model with parameter, we want to discover the parameter that capitalize on the posterior probability P(X|θ) In K-means clustering,*X*– observed data $[(x]_i)_{i=1}^{n}$. The clustering of the observed data points θ and their associated centres μ_j .EM algorithms is given in the following steps.

- Initiate with a hypothesis *θ*.
- **(Expectation step)** Calculate the posterior probability *P(X|θ)*.
- **(Maximization step)** Classify the perceived information conferring to the probability, and fill in the hypothesis consequently.
- The method is repeated till the theory congregates.

2.2.6 Hybrid (GMM based k-means) clustering algorithm

K-means algorithms only reveal information about the cluster membership. However, the EM algorithm can be modified to calculate the parameters μ, π and σ.

We assume, the likelihood $P(x_i|S_j)$ follows a Gaussian distribution

$$P(x_i|S_j) \sim \pi_j G\,(||x_i\text{-}\mu_j||,\sigma_j) \qquad (13)$$

Where G is the Gaussian probability density distribution. The actual probability is calculated as following.

$$P(x_i|S_j) = \pi_j G\,(||x_i\text{-}\mu_j||,\sigma_j)/\,\Sigma_k(\pi_k G\,(||x_i\text{-}\mu_j||,\sigma_j)) \qquad (14)$$

where μ is the weighted averages of all *x*, π is the normalized ratio of the sums and σ is the weighted standard deviation and are given by

$$.\mu_j = (\,\Sigma_i P(x_i|S_j)x_i\,)\,/\,R_k \qquad (15)$$

$$\sigma_j^2 = (\,\Sigma_i P(x_i|S_j)||x_i\text{-}\mu_j||\,)\,/\,IR_k \qquad (16)$$

$$\pi_j = Rj\,/\,(\Sigma k R_k) \qquad (17)$$

$$R_j = \Sigma_i P(x_i|S_j) \qquad (18)$$

3. Experimental Results

The section is divided into three parts i.e. feature extraction, classification, and retrieval

3.1 Feature Extraction

Colour images are used to extract the colour and texture features and also for resemblance matching because maximum images in the world are colour images. Hence, two of the most important features that were taken into consideration while developing a CBIR method are colour and

Figure 3. Query Image.

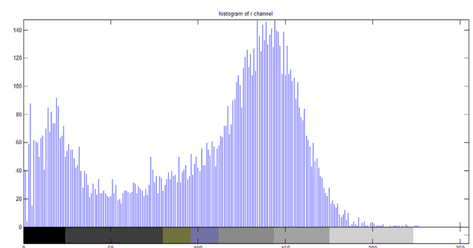

Figure 4. Histogram of Red Channel.

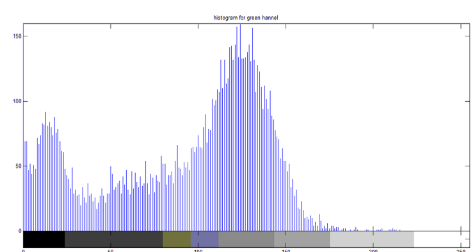

Figure 5. Histogram of Green Channel.

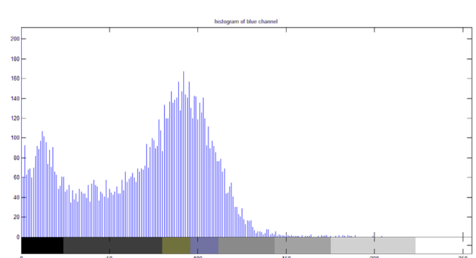

Figure 6. Histogram of Blue Channel.

texture features. By taking images from WANg database different classes are formulated. We divided the images into different categories based on their similarities for example butterflies, horses, flowers humans and feature extraction was performed on them. To test the system, we have selected a indiscriminate image from the Butterfly class. We later extracted the image features for all the 10 selected images as well as for the query image. We have considered Figure 3 as the query image and extracted the colour and texture features of the same. The Figures 4, 5, 6 shows the histograms representing red, green and blue colour extraction. The results for comparison of three images by colour and texture extraction features are given in (Table 1).

3.2. K-means Clustering

When the image has been applied by the clustering algorithm, record is prepared which decreases the time spent for retrieving images. The clustering phase is also used to avoid the system computation complexity. Due to this the entire database need not be explored. The proposed method marginally increases the performance of

Table 1. Comparison between Sample and Similar Image from the WANG Database on the basis of Texture and Colour

IMAGE	ENERGY		CORRELATION		CONTRAST		HOMOGETNITY		ENTROPY
	MIN	MAX	MIN	MAX	MIN	MAX	MIN	MAX	
SAMPLE IMAGE	0.0739	0.1785	0.0188	0.8068	1.4175	8.4796	0.5181	0.7976	6.9564
SIMILAR IMAGE	0.0274	0.0915	0.0418	0.8686	1.0455	8.0825	0.4229	0.8153	7.2367
IRRELEVEANT IMAGE	0.0362	0.1238	0.0967	0.0967	0.5333	10.0822	0.5001	0.9319	7.1987

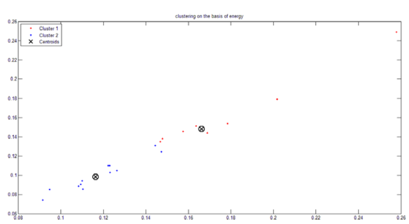

Figure 7. Clustering on the Basis of Energy.

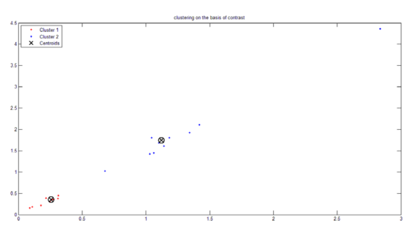

Figure 8. Clustering on the Basis of Contrast.

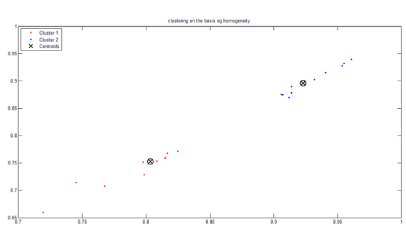

Figure 9. Clustering on the Basis of Homogeneity.

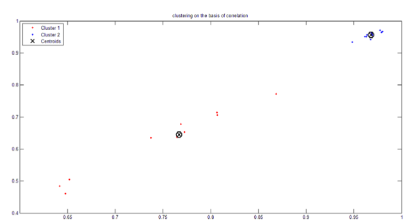

Figure 10. Clustering on the Basis of Correlation.

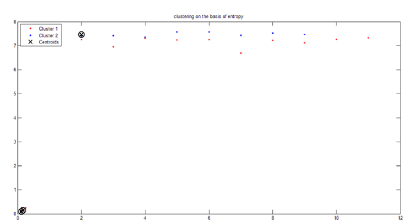

Figure 11. Clustering on the Basis of Entropy.

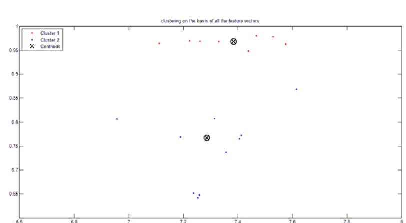

Figure 12. Clustering on the Basis of all Feature Vectors.

Figure 13. Query image.

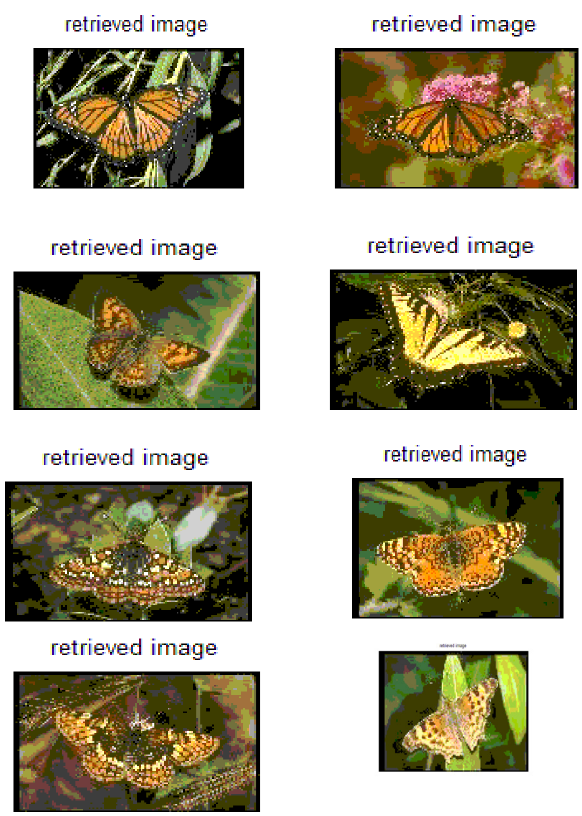

Figure 14. Retrieved images.

the CBIR system as linked to other methods which use k means clustering. The clustering of images from the database by using different colour and texture features is shown in the following Figures 7-12.

3.3. Retrieval

The following 8 images in Figure .14 were retrieved, when a query image Figure 13 was given to the CBIR system.

The most commonly applied performance measures in the CBIR are precision and recall. Precision measures the retrieval image accuracy. Recall measures the retrieval robustness. The equation and the obtained result are given below:

Precision = Number of relevant images retrieved / Total number of images retrieved = 0.98

Recall=Number of relevant images retrieved /Number of relevant images in the database = 0.95

4. Conclusion

In this study, WANG database is used for CBIR field. We created a new database for our study and included 100 images in RGB colour space from WANG database. The colour and texture feature extraction was done as a pre-processing step. We used the colour histogram and gray level co-occurrence matrix for colour feature extraction and texture feature extraction respectively. Instead of comparing query image with all the images we compared the query image with a small subset by using the proposed method for clustering, i.e., Gaussian mixture model based k-means clustering algorithm. The Hybrid Proposed Mechanism able to retrieve the query image with more accuracy.

5. References

1. Butt S, Tariq M. Visual feature extraction for content-based image, 2013.
2. Wang J Z. Wang database; Available from:http://wang.ist.psu.edu/. Jan ,2016.
3. Karamizadeh F, Zolfagharifar AZ, Using the Clustering Algorithms and Rule-based of Data Mining to Identify Affecting Factors in the Profit and Loss of Third Party Insurance, Insurance Company Auto, Indian Journal of Science and Technology.2016 Feb; 9(7): 1–9.
4. Vora P, Oza B. A survey on k-mean clustering and particle swarm optimization. International Journal of Science Model Engineering (IJISME), 2013; 1(3): 24–6.
5. Younus Z S, Mohamad D, Saba T, Alkawaz M H, Rehman A, Al-Rodhaan M, Al-Dhelaan A. Content-based image retrieval using PSO and k-means clustering algorithm, Journal of Geo Sciences. 2014;8(8): 6211–24.
6. Dharmarajan A, Velmurugan T. Lung Cancer Data Analysis by k-means and Farthest First Clustering Algorithms, Indian Journal of Science and Technology.2015; July, 8(15):1-8.
7. Chen J. Perceptually-based texture and color features for image segmentation and retrieval, University of Northwestern: New York, 2003.
8. Ahmed G F, Barskar R. A study on different image retrieval techniques in image processing. International Journal of Soft Computing and Engineering (IJSCE). 2011; 1(4): 247–51.

9. Koskela M. Interactive image retrieval using self-organizing maps, in Computer Science and Engineering ,Helsinki University of Technology: Espoo, 2003.
10. Robotka Z, Zempleni A. Image retrieval using Gaussian mixture models , Annales University Sci. Budapest., Sect. Comp. 2009; 31, p. 93–105.
11. Varghese T A. Performance enhanced optimization based image retrieval system. International Journal of Computer Applications (IJCA). 2010; 1, p. 31–4.
12. Al-Hamadani I. Fast access image retrieval system, University of Mosul Iraq: Iraq, 2006.
13. Shanmugapriya N, Nallusamy R. A new content based image retrieval system using GMM and relevance feedback, Journal of Computer Science. 2014; 10 (2): 330-40.
14. Permuter H, Francos J, Jermyn I H. Gaussian mixture models of texture and colourfor image database, Proceedings of the International Conference on Acoustics, Speech and Signal Processing, ICASSP'03.2003; 3, p. 569–72.