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An Efficient QBIR system using Adaptive segmentation and multiple features

Neelima.N^a, E.Sreenivasa Reddy^b, Kalpitha.N^c

^aDepartment of Electronics & Communications, Jain University, Bangalore, India- 562112.

^cDepartment of Computer Science Engineering, Jain University, Bangalore, India – 562112.

^bDepartment of Computer Science Engineering, Acharya Nagarjuna University, Guntur, India- 522007.

Abstract

Query by Image Content Retrieval abbreviated as QBIR, has become new thirst now a days. By using this systems, user can retrieve the similar images of an already existed image (or) a rough sketch (or) a symbolic representation. To make more efficient and user friendly QBIR multiple features are employed. This paper proposes a novel approach for image retrieval using adaptive k-means clustering and shape, texture features. The experimental results portray the performance of the proposed retrieval system in terms of better precision. To evaluate the proposed method COIL and MPEG-7 shape 1 datasets are used.

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2D to 3D conversion, Segmentation, Occlusion elimination, Adaptive K-means.

1. Introduction

QBIR, being one of the content based image retrieval search methods which analyses the contents of the image instead of keywords (or) tags. “Surfing” and “Searching” are the two popular terms now days in reality. Varieties of search techniques available for the users such as text based, image based and graphics based. Based on query the user may surf for his favorite holiday spot or search for similar images. Irrespective of searching or surfing at the end the user wants to retrieve the desirable content of his expected choice. Earlier retrieval techniques were mostly text based which were limited because of improvement in digital media. In general CBIR systems make use of shape, texture and colour features of images and retrieve the similar images based on the similarity distance comparison. To improve the efficiency of the system multiple features can be combined as a feature vector and can be used. The features of query image are compared to the features of the database images. Its applications extend to the fields such as scientific databases, Medical database, Surveillance systems and Digital photo albums. Segmentation divides the images into homogenous [1] regions which is especially used in retrieving the similar images. In the conventional K-means algorithm [2], the input

data are automatically grouped into corresponding clusters. The traditional k-mean type algorithm is limited to numeric data. The Adaptive K-means [3] has several advantages such that it is fast in converging and also works with numeric and categorical features. It proposes a new cost function and distance measure based on co-occurrence of values. Several systems [5] were proposed with different features. In the past decades, several CBIR based on multiple features were proposed. We propose an approach for image retrieval with multiple features.

The block diagram of the proposed retrieval system is shown in Fig.1. Initially all the images in the database are segmented by using Adaptive K-Means Clustering and shape, texture features are extracted. When the user enters his choice of query image, it is segmented by using adaptive k-means algorithm to classify them into clusters. Shape, texture features are extracted and stored as feature vector. The similar images are retrieved according to the similarity estimate the distance between the feature vector of query and database images. The images are arranged and displayed in ascending order of the similarity distance.

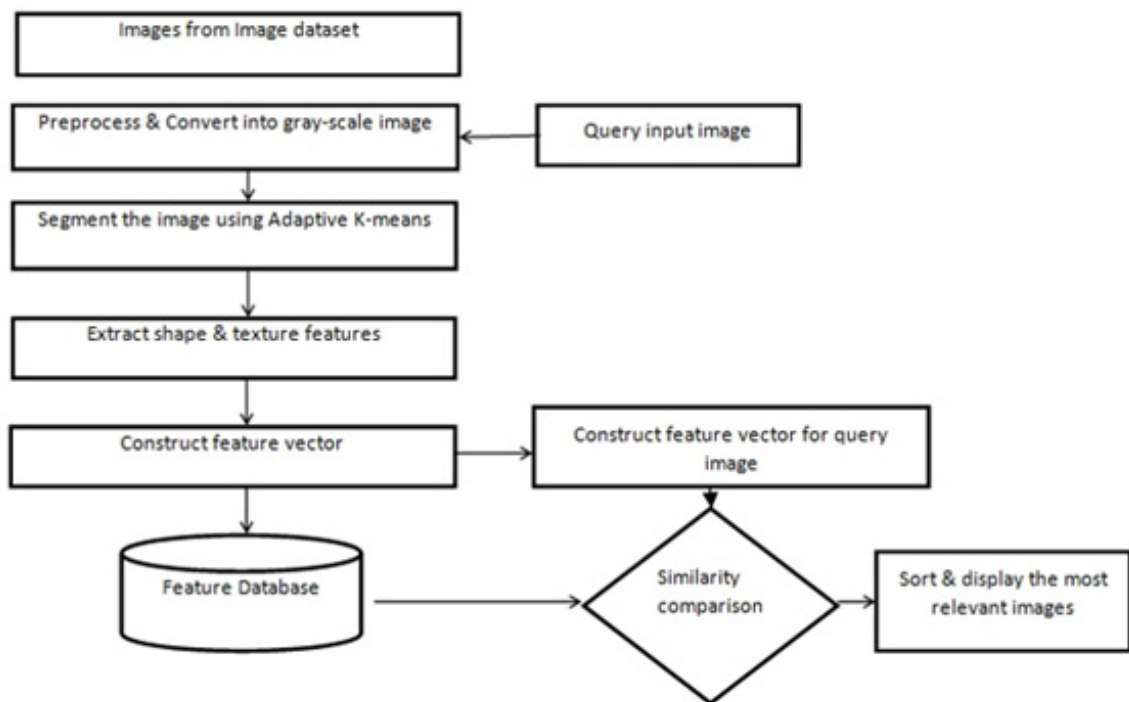


Fig. 1. Block diagram of the proposed method

2. Adaptive K-means Segmentation

The Adaptive K-means clustering is the most widely used technique for image segmentation. The process starts by choosing randomly k points as cluster centers. All the objects are assigned to any one of the center based on the similarity measure. For each cluster again a new center is calculated by taking average of all the features in the feature vector. The K-means algorithm is an iterative technique that is used to partition an image into K clusters. In real time systems k-means clustering is used to partition n observations into k clusters in which

each cluster is assigned to a cluster based on the nearest mean. The proposed method uses adaptive k-means algorithm which is given as below.

First K cluster centers are defined randomly (or) based on some pre-defined criteria.

- Each pixel in the image is assigned to any one of the cluster based on the minimum distance between the pixel and cluster center.
- After assigning, the new cluster centers are computed by averaging all of the pixels in the cluster.
- The above two steps are repeated until no pixels in the clusters change. This condition is known as convergence.

Consider a set of observations (x_1, x_2, \dots, x_n) , where each observation is represented by a d-dimensional real vector. The main aim of k-means clustering is to partition the observations into k sets $(k < n)$ $S = \{S_1, S_2, \dots, S_k\}$ which is to minimize the within-cluster sum of squares which is given in Eq. (1).

$$\arg \min \sum_{i=1}^k \sum_{x_j \in S_i} \|X_j - \mu_i\|^2 \quad (1)$$

3. Feature Selection

In QBIR systems, selection of features plays a vital role in the performance. Shape features were extracted by fourier descriptor and radial chebyshev moments are used to extract texture features.

3.1 Radial Chebyshev moments

For a given function $f(x,y)$ the general moment function is defined by Eq.(2).

$$\Phi_{pq} = \psi \iint xy_{pq} (x,y) f(x,y) dx dy \quad (2)$$

These moments are effectively used in image analysis [5]. The Radial Chebyshev moments are calculated according to [4] of an image of size $N \times N$ given in Eq. (3) and Eq. (4).

$$t_0(x) = 1 \text{ and } t_1(x) = \frac{2x-N+1}{N} \quad (3)$$

$$t_m(x) = \frac{[(2m-1)t_1(x)t_{m-1}(x) - (m-1)(1 - \frac{m-1}{2})t_{m-2}(x)]}{m} \quad (4)$$

The radial chebyshev moments for the order p and repetition q is given in Eq. (5)

$$S_{pq} = \frac{1}{2\pi\rho(p,m)} \sum_{r=0}^{m-1} \sum_{\theta=0}^{2\pi} t_p(r) e^{-jq\theta} f(r, \theta) \quad (5)$$

$$\text{Where } x = \frac{rN}{2(m-1)} \cos\theta + \frac{N}{2} \text{ and } y = \frac{rN}{2(m-1)} \sin\theta + \frac{N}{2}$$

3.2 Fourier descriptor

In general, Fourier descriptor method involves in computation of boundary pixels, use of shape signature function [6]. By using this contour based descriptions can be done [7]. With these boundary pixels, a pixel set can be formed and is given in Eq. (6).

$$P = \{(x(t), y(t)) | t \in [1, N]\} \quad (6)$$

Where N is the number of boundary pixels. Shape signature functions are used to construct shape signatures from the boundary pixel set. Complex coordinates, curvature function, cumulative angular function, and centroid distance are the commonly used shape signature functions. The coordinate of the centroid is (X_c, Y_c) for the shape set of P is given in Eq.(7)

$$X_c = \frac{1}{N} \sum_{t=0}^{N-1} X(t) \text{ and } Y_c = \frac{1}{N} \sum_{t=0}^{N-1} Y(t) \quad (7)$$

The distance from the centroid to each pixel in the set is given in Eq. (8).

$$r(t) = \sqrt{[x(t) - x_c]^2 + [y(t) - y_c]^2} \quad (8)$$

Only the magnitude of the coefficients are considered from the above equation and the phase is ignored. Consider b_n gives the fourier transformed coefficients which were standardized and is given by Eq. (9).

$$b_n = \left| \frac{a_n}{a_0} \right| \quad (9)$$

Where b_n is invariant to translation, scaling, rotation from a_0 . The computation of Fourier descriptor is used to compute shape features known as b_n . The shape feature vector is given in Eq. (10).

$$FD = \left\{ b_i \mid i \in \left[0, \frac{N}{2} - 1\right] \right\} \quad (10)$$

4. Similarity distance measures

The euclidean distance [8] between the feature vectors of query image (Q_i) and the images in dataset (Db_i) is given by Eq. (11)

$$\sqrt{\sum_{i=1}^n (Q_i - Db_i)^2} \quad (11)$$

The city block distance [8] between the feature vectors of query image (Q_i) and the images in dataset (Db_i) is given by Eq. (12)

$$\sum_{i=1}^n |Q_i - Db_i| \quad (12)$$

5. Results

To evaluate the performance of the proposed system two data sets were considered from Columbia Object Image Library (COIL-100) and MPEG-7 CE shape-1 set. The first set consists of 10 different classes of images, shown in Fig.2. Each class consists 72 images of an object with various orientations. The second set consists of 10 different categories considered from MPEG-7 CE shape -1 database, with each category consists of 20 images. This data set is shown in Fig. 3. The performance analysis of the proposed method for the two datasets is shown in Fig.4. The retrieval analysis with respect to the existing system [9] for the first data set is shown in Table 1. The retrieval performance of the system is evaluated terms of precision. The precision [8] is defined as

$$\text{Precision} = \frac{\text{Number of relevant retrieved images}}{\text{Total number of Retrieved images}}$$



Fig. 2. The query images used in data set 1 from COIL database

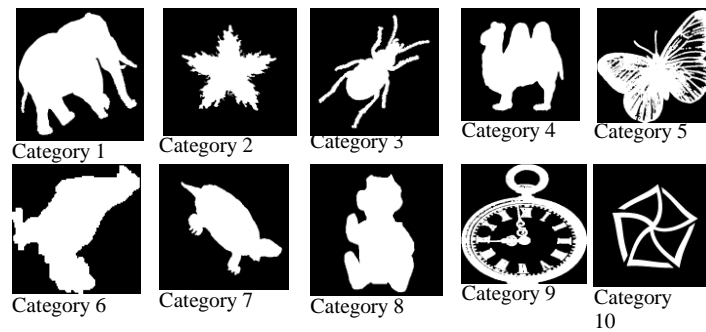


Fig. 3. The query images used in data set 2 from MPEG database

Table 1. Retrieval accuracy comparison of the proposed and existing systems

| Image Category | Existing System | Proposed System |
|-------------------|-----------------|-----------------|
| Category 1 | 100 | 100 |
| Category 2 | 84 | 69.44 |
| Category 3 | 53 | 68.05 |
| Category 4 | 67 | 80.5 |
| Category 5 | 83 | 100 |
| Category 6 | 100 | 100 |
| Category 7 | 99 | 100 |
| Category 8 | 99 | 100 |
| Category 9 | 70 | 83.33 |
| Category 10 | 100 | 100 |
| Average precision | 85.5 | 90.13 |

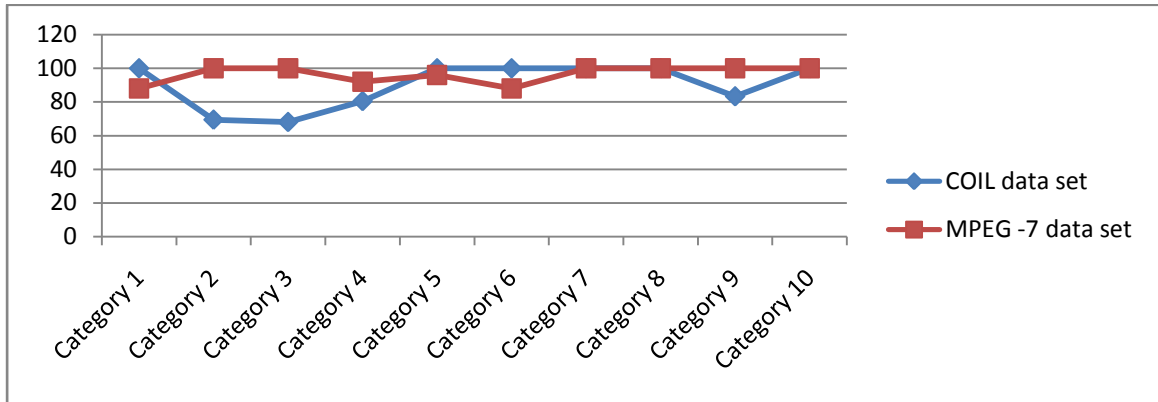


Fig. 4. Performance analysis for the proposed method in different data sets

6. Conclusion

The algorithm which is implemented in this paper proves to be the perfect solution when tested on the various images. Image features such as shape and texture were extracted by making use of Fourier descriptors and radial Chebyshev moments. The choice of these features helps to arrive at better performance in terms of retrieval. For similarity comparison city block and Euclidean distances were considered. The experimental results depict that the City block distance provides better results. Hence we conclude that the proposed system in this paper which uses Radial Chebyshev moments and Fourier descriptors as features with city block distance as similarity measure provides better precision for all the categories considered.

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