Development of the Content Based Image Retrieval Using Color, Texture and Edge Features

Sindhu S[#1], Mr. C O Prakash[#2]

[#1]*M.Tech Student, Department of ISE, PESIT, Bangalore ,India*
[#2]*Assistant Professor , Department of ISE, PESIT, Bangalore ,India*

Abstract— **The purpose of this paper is to describe solution to the problem of designing a Content Based Image Retrieval (CBIR) system. CBIR has become an active and fast-advancing research area in image retrieval in the last decade. With the rapid development of computer technology, the amount of digital imagery data is rapidly increasing. There is an inevitable need for efficient methods that can help in searching for and retrieving the visual information that a user is interested in. The manual annotation of images is becoming more and more an infeasible process. An ever flourishing retrieval technique is content based image retrieval (CBIR), where the visual contents found in the images are exploited for representing and retrieving the images. The increased need of content based image retrieval technique can be found in a number of different domains such as Data Mining, Education, Medical, Weather forecasting, Remote Sensing etc. This paper presents the content based image retrieval using features like color, texture and edge histogram. The combinations of these three techniques are used and the Euclidian distance is calculated for the every feature is added and the averages are made. Our software application built using OpenCv with Microsoft visual studio 2010, with an image database. It extracts color, texture and edge features of the input image and images in the database as the basis of comparison and retrieval.**

Keywords— ***Content-based image retrieval (CBIR), HSV Color Space, GLCM, EHD.***

I. INTRODUCTION

Due to the low cost of scanners and storage devices, more and more digital images are being captured and stored. As a result, large image databases are being created and used in a number of applications such as entertainment, art galleries, fashion design, education, medicine, industry, etc. These databases typically consist of thousands of images, taking up gigabytes of memory space. The large volume of these images makes it difficult for a user to browse through the entire database. Therefore, developing proper tools for the retrieval image from large image collections is challenging.

In earlier retrieval systems, images are described using plain text and retrieval is based on the text description [9]. Two different types of approaches in Image Retrieval, 1.Text based Image Retrieval and 2.Content based Image Retrieval. In the text-based system: human intervention is required to describe and tag the contents of the images in terms of a selected set of captions and keywords shown in fig 1. The advantages of text-based system are easy to implement, fast retrieval and web image search. The Limitations of text-based system are manual annotation is not always available and is impossible for a large DB, manual annotation is not accurate, there are inconsistencies between user textual queries and image annotations or descriptors. Images are identified by textual descriptors called metadata.

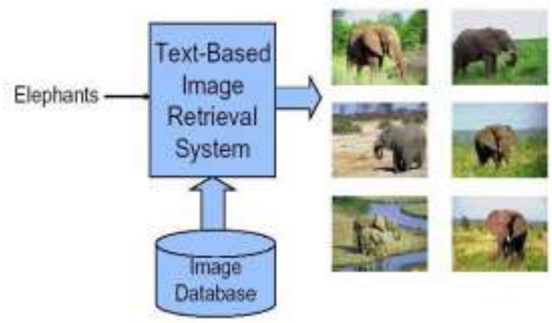

Fig 1: Text Based Image Retrieval

To reduce the inconsistency problem, the image retrieval is carried out according to the image contents; such strategy is called content-based image retrieval.
2. Content-Based Approach: Images can be search based on visual features, such as color, texture, and edge information and find the similarities of images using Euclidian distance between features shown in fig 2.

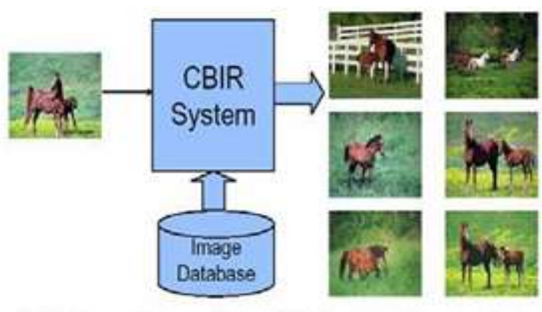

Fig 2: Content based image retrieval

II. RELATED WORK

CBIR has become an active and fast-advancing research area in image retrieval in the last decade. Global image properties based, local image properties based, region-level features based, relevance feedback, and semantic based. Initially, developed algorithms exploit the low-level features of the image such as color, texture, edge and shape of an object to help retrieve images that are most satisfied to the users. They are easy to implement and perform well for images that are either simple or contain few semantic contents.

The difference between the user's information need and the image representation is called the semantic gap in CBIR systems. The limited retrieval accuracy of image centric retrieval systems is essentially due to the inherent semantic gap between users. In order to reduce the gap, the interactive relevance feedback system is introduced into CBIR. The basic idea behind relevance feedback is to incorporate human perception subjectivity into the query process and provide users with the opportunity to evaluate the retrieval results. The similarity measures are automatically refined on the basis of these evaluations.

There are various approaches are present for Content Based Image Retrieval. Some of the important literature which covers the more important CBIR System is discussed below. Chin-Chin Lai et.al. [1] have proposed an interactive genetic algorithm (IGA) to reduce the gap between the retrieval results and the users' expectation .They have used color attributes like the mean value, standard deviation, and image bitmap .They have also used texture features like the entropy based on the gray level co-occurrence matrix and the edge histogram . They achieved better results.

In [2], a CBIR scheme based on the global and local color distributions in an image is presented. Liapis and Tziritas [3] explored image retrieval mechanisms based on a combination of texture and color features. Texture features are extracted using discrete wavelet frame analysis method.

Chun et al. [4] proposed a CBIR method based on an efficient combination of multiresolution color and texture features based CBIR. Their colors, autocorrelograms features of the hue and saturation component images in HSV color space are used. As its texture features, block difference of inverse probabilities and block variation of local correlation coefficient moments of the value component image are adopted. The color and texture features are extracted in multiresolution wavelet domain and then combined.

In order to well model the high-level concepts in an image and user's subjectivity, recent approaches introduce human computer interaction into CBIR. Takagi et al. [5] evaluated the performance of the IGA-based image retrieval system that uses wavelet coefficients to represent physical features of images. Cho applied IGA to solve the problems of fashion design and emotion-based image retrieval. They used wavelet transform to extract image features and Interactive genetic algorithm to search the image that the user has in mind. When the user gives appropriate fitness to what she or he wants, the system provides the images selected based on the user's evaluation. Arevalillo-Herráez et al. [6] introduced a new hybrid approach to relevance feedback CBIR. Their technique combines an IGA with an extended nearest neighbour approach to reduce the existing gap between the high-level semantic contents of images and the information provided by their low level descriptors. Under the situation that the target is unknown, face image retrieval has particularity. Shi et al. [7] proposed an IGA-based approach which incorporates an adjust function and a support vector machine. Their method can prevent the optimal solution from losing, accelerate the convergence of IGA, and raise retrieval performance.

III. IMAGE FEATURES

A. Color Feature Extraction

A color image can be represented using three primaries of a color space. Since the RGB color space does not correspond to the human way of perceiving the colors, we used the HSV color space in our approach [9]. HSV is an intuitive color space in the sense that each component contributes directly to visual perception, and it is common for image retrieval systems. Hue is used to distinguish colors or represents a pure color, where as saturation gives a measure of the percentage or amount of white light added to a pure color. Value refers to the perceived light intensity or measures brightness. The very important advantages of HSV color space are as follows: good compatibility with human intuition and there is a separability of chromatic and achromatic components.

The color distribution of pixels in an image contains sufficient information. There are Global color properties and Local color properties of an image. We can use following two features to represent the global properties of an image. The mean of pixel colors states the principal color of the image, and the standard deviation of pixel colors represents the variation of pixel colors in an image. The variation degree of pixel colors in an image is called the color complexity of the image [8].

Global Color Properties:

The mean (μ) and the standard deviation (σ) of a color image are defined as follows:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} Pi \qquad (1)$$

$$\sigma = \sqrt[2]{\frac{1}{N-1}\sum_{i=1}^{N}(Pi-\mu)^2} \qquad (2)$$

Where $\mu = [\mu H, \mu S, \mu V]\ T$ and $\sigma = [\sigma H, \sigma S, \sigma V]\ T$, each component of μ and σ indicates the HSV information, and Pi indicates the *i*th pixel of an image.

Local Color Properties:

The local color properties in an image play also an important role to improve the retrieval performance. Hence, a feature called binary bitmap can be used to capture the local color information of an image.

There are three steps to generate the image binary bitmap.

1. First step: Divides an image into several nonoverlapping blocks.
   Let $Bj = \{b1, b2, \dots, bk\}$ be the jth block of the image, where $1 \le j \le m$;
   k represents the total number of pixels in the block, and m is the total number of blocks in the image.

2. The Second step is to compute the mean value for each block.
   Let μBj be the mean value of the block Bj, which is defined as follows:

$$\mu Bj = \frac{1}{k}\sum_{i=1}^{k} bi \qquad (3)$$

   where $\mu Bj = [\mu HBj, \mu SBj, \mu VBj]^T$.

3. Final step, comparing μBj with the image mean value (μ) is performed to determine the characteristic of the block Bj and to generate the image binary bitmap.

Hence, suppose that $I = [IH, IS, IV]$ is the binary bitmap of the given image. Each component in I is expressed as $IH = [IH1, IH2, \dots, IHm]$, $IS = [IS1, IS2, \dots, ISm]$, and $IV = [IV1, IV2, \dots, IVm]$, respectively. The entries are represented by

$$IH_j = \begin{cases} 1, & \text{if } \mu H_{B_j} \ge \mu H \\ 0, & \text{otherwise} \end{cases} \qquad (4)$$

$$IS_j = \begin{cases} 1, & \text{if } \mu S_{B_j} \ge \mu S \\ 0, & \text{otherwise} \end{cases} \qquad (5)$$

$$IV_j = \begin{cases} 1, & \text{if } \mu V_{B_j} \ge \mu V \\ 0, & \text{otherwise.} \end{cases} \qquad (6)$$

B. Texture Properties

Texture is an important attribute that refers to innate surface properties of an object and their relationship to the surrounding environment. We use a gray level co-occurrence matrix (GLCM), which is simple and effective method for representing texture.

GLCM creates a matrix with the directions and distances between pixels, and then extracts meaningful statistics from the matrix as texture features. GLCM textures features commonly used are shown in the following The GLCM represents the probability p (i, j; d, θ) that two pixels in an image, which are located with distance d and angle θ, have gray levels i and j. The GLCM is mathematically defined as follows:

$$p(i,j|d,\theta) = \#\{(x1,y1)(x2,y2)|g(x1,y1) = i, g(x2.y2) = j, |(x1,y1) - (x2,y2)| = d, \angle((x1,y1)) = \theta\} \qquad (7)$$

where # denotes the number of occurrences inside the window, with i and j being the intensity levels of the first pixel and the second pixel at positions ($x1$, $y1$) and ($x2$, $y2$), respectively.

In order to simplify and reduce the computation effort, we computed the GLCM according to directions (i.e., θ = 0°, 90°, 45°,135°) with a given distance d (= 1) and calculated the GLCM features entropy, energy and contrast, which are used most frequently in the literature.

The entropy (E) is used to capture the textural information in an image and is defined as follows:

$$\text{Entropy } S = \sum\sum p(x, y) \log p(x, y) \qquad (8)$$

Where $p(x, y)$ is the GLCM. Entropy gives a measure of complexity of the image. Complex textures tend to have higher entropy.

The Energy (E) is used to of homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight in an image and is defined as follows:

$$\text{Energy } E = p(x, y)^2 \qquad (9)$$

The Contrast is the main diagonal near the moment of inertia, which measure the value of the matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadow depth. Contrast is large means texture is deeper and is defined as follows:

$$\text{Contrast } I = \sum\sum(x - y)^2\, p(x, y) \qquad (10)$$

C. Edge feature extraction

Edges in images constitute an important feature to represent their content. Human eyes are very sensitive to edge features for image perception. An edge histogram in the image space represents the frequency and the directionality of the brightness changes in the image and adopts the edge histogram descriptor (EHD) [12] to describe edge distribution with a histogram based on local edge distribution in an image.

The extraction process of EHD consists of the following stages.

1) An image is divided into 4 × 4 subimages.
2) Each subimage is further partitioned into nonoverlapping image blocks with a small size.
3) The edges in each image block are categorized into five types: vertical, horizontal, 45◦ diagonal, 135◦ diagonal and nondirectional edges.

4) Thus, the histogram for each subimage represents the relative frequency of occurrence of the five types of edges in the corresponding subimage.
5) After examining all image blocks in the sub image, the five-bin values are normalized by the total number of blocks in the sub image.

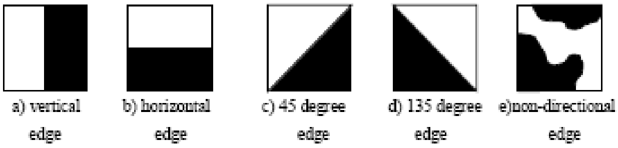

Fig 3: Types of Edges

IV. ALGORITHM

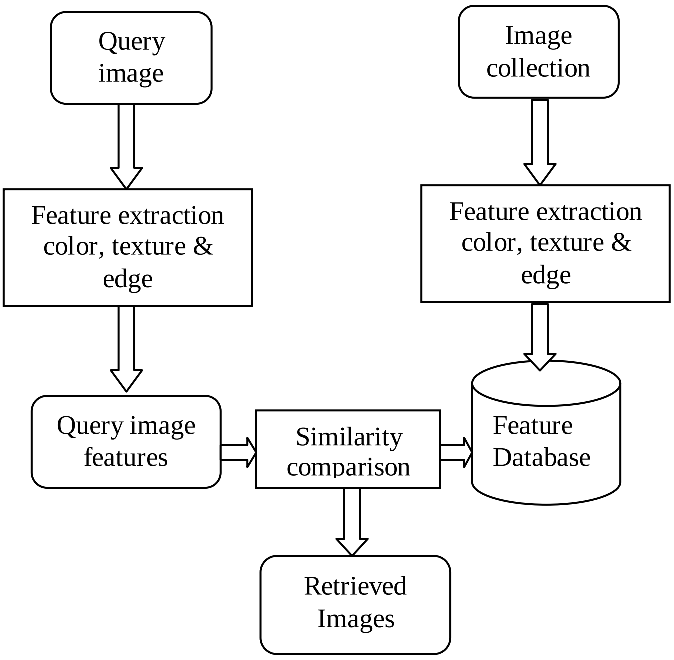

Fig 4: Proposed flow chart

We design a content based image retrieval system based using color, texture and edge features, as shown in Fig. 4. Our system operates in four phases.

1) **Querying**: The user provides a sample image as the query for the system.

2) **Feature Extraction**: Extract low-level visual features for user query image and database images.

3) **Similarity Computation**: The system computes the similarity between the user query image and the database image according to low-level visual features.

Euclidian Distance Measure:

Similarity Measurement is done using Euclidian Distance between an image D, which is present in the data base and query image Q can be given as,

$$Euclidian\ Distance = \sqrt{\sum_{i=1}^{N} (Di - Qi)^2} \qquad (11)$$

Where, *Di* and Q*i* are the feature vectors of image D and query image Q respectively with size n.

4) **Retrieval**: The system retrieves and presents a sequence of images ranked in decreasing order of similarity. As a result, the user is able to find relevant images by getting the top-ranked images first and calculate retrieval performance.

V. EXPERIMENTAL SETUP AND RESULTS

This chapter is used to explain result analysis. To get desired Result,P-4,genuine Intel, 2GB RAM, 40GB hard Disk, Windows 7, OpenCv 2.4.3 with Microsoft Visual Studio 2010.

Retrieval Performance Effectiveness

The precision and recall values are measured by simulating retrieval scenario. The retrieval effectiveness can be defined in terms of precision and recall rates. For each query image, relevant images are considered to be those and only those which belong to the same category as the query image. Based on this concept, the retrieval precision and recall are defined as

$$Precision = \frac{N_{A(q)}}{N_{R(q)}} \qquad (12)$$

$$Recall = \frac{N_{A(q)}}{N_t} \qquad (13)$$

Where *NA* (*q*) denotes the number of relevant images similar to the query,
NR (*q*) indicates the number of images retrieved by the system in response to the query, and N_t represents the total number of relevant images available in the database.

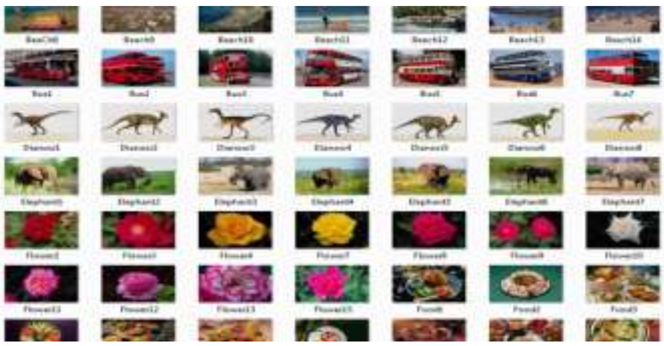

Fig 5: Sample images of each category of the image database

Fig 6: CBIR Output for user query image1

Fig 7: CBIR Output for user query image2

Fig 8: CBIR Output for user query image3

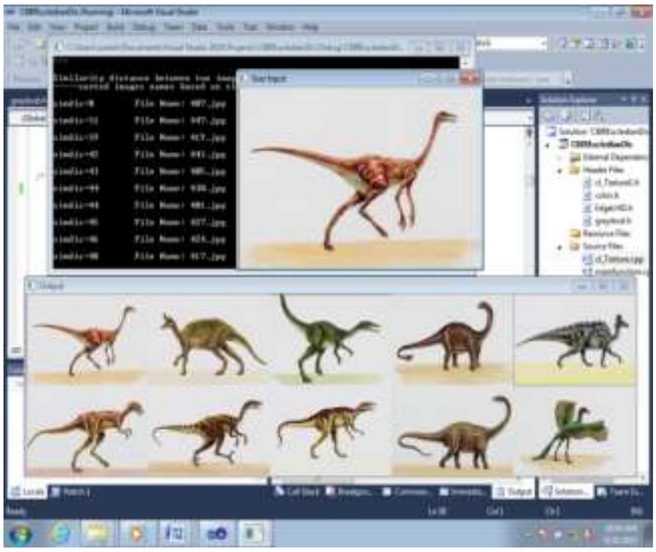

Fig 9: CBIR Output for user query image4

Category	Precision	Recall
Dinosaurs	98	19.6
Buses	76	15.2
Flowers	98	19.6
Horses	55	11
Mountains	50	10
Food	65	13
Elephants	50	10

Table 1: Precision and recall values

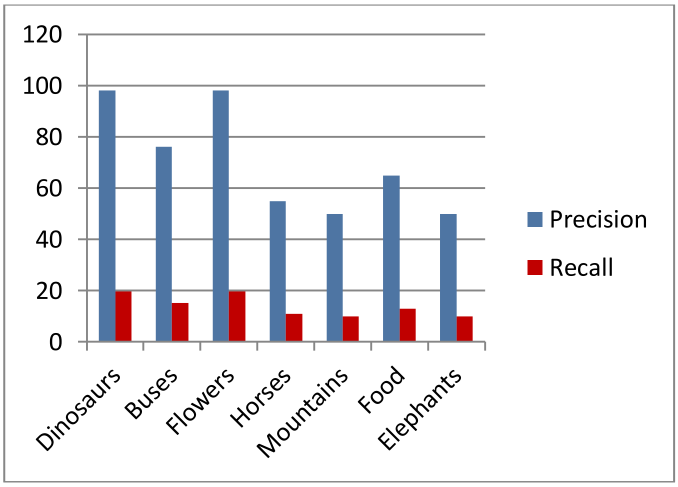

Fig 10: Average Precision & Recall values

VI. CONCLUSION AND FUTURE ENHANCEMENT

Depending upon the application area, we are using the CBIR method for the retrieval of the images. A Database consists of different types of images has implemented on the system. Different Features such as color, texture and edge. From the experimental result it is seen that combined features can give better performance than the single feature. Only one feature is insufficient for proper retrieval of the image, so in the proposed method along with the low level feature color and another low level feature texture and Edge histogram is used.
The color distributions, the mean value, the standard deviation, and image bitmap are used as color information of an image. The entropy based on the GLCM and edge histogram are considered as texture descriptors to help characterize the images. Future work is considering more low-level image descriptors or high-level semantics to improve the retrieval performance and user's expectation.

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