

# Content Based Image Retrieval using Color, Shape and Texture Extraction Techniques

Nupur Kandalkar, Arvind Mani, Garima Pandey, Jignesh Soni

**Abstract**— Images contain information in a very dense and complex form, which a human eye only after years of training can extract and understand. In Content-Based Image Retrieval (CBIR), visual features such as color, shape and texture are extracted to characterize images. How to extract ideal features that can reflect the intrinsic content of the images as complete as possible is still a challenging problem. This paper mainly focuses on representing the image in terms of low level features extracted from the image. These low level features primarily constitute colour, shape and texture features. By processing the extracted features instead of the entire image, reduces the memory requirements as well as the computational time required to process the image. Each of the features is represented using one or more feature descriptors. During the retrieval, features and descriptors of the query are compared to those of the images in the database in order to rank each indexed image according to its distance to the query. The distances of the various database images to the query image are sorted in order to calculate the similarity between them. The patterns from the candidates are retrieved from database by comparing the distance of their feature vectors. The CBIR technology has been used in several day-to-day applications such as fingerprint identification, biodiversity information systems, digital libraries, crime prevention, medicine, historical research, biomedical field etc. In this paper the different colour, shape and texture feature extraction techniques have been studied and implemented in order to obtain the desired results. The results also prove that only colour, shape or texture features are insufficient to describe the entire image, and thus a combination of two or more feature extraction techniques is required to obtain best results.

**Index Terms**— Image Processing, CBIR, Feature extraction, Feature matching, Image similarities.

## I. INTRODUCTION

Content Based Image Retrieval (CBIR) is a technique that helps to access and arrange the digital images from a large collection of databases by using the images features. In modern era with the development of social networks many digital images are uploaded every day. In order to handle this huge data new techniques are very essential. CBIR is such a technique that will ease the data handling and the user can easily access the data. The increasing amount of digitally produced images requires new methods to archive and access. The images can be retrieved using color, texture and shape. The most important feature in retrieving an image is color. There are so many methods to retrieve the color. They include color histogram, color moments, autocorrelogram etc. Color histogram is the widely used method for color feature extraction. Color histogram method does not store the spatial

information and also it is not invariant to scaling. Color moments provide a measurement for color similarity between images. Moments are invariant to scaling and rotation. The first four moments are usually calculated. Color correlogram provides the probability of finding color pairs at a particular pixel distance. Color correlogram gives better output than color histogram because the color correlogram provides the spatial information. Texture is retrieved using GLCM, entropy etc. shape is the next used image feature for retrieval. Shape is known as an important cue for human beings to identify and recognize the real-world objects, whose purpose is to encode simple geometrical forms such as straight lines in different directions. Shape feature extraction techniques can be broadly classified into two groups, viz., contour based and region based methods. The former calculates shape features only from the boundary of the shape, while the latter method extracts features from the entire region.

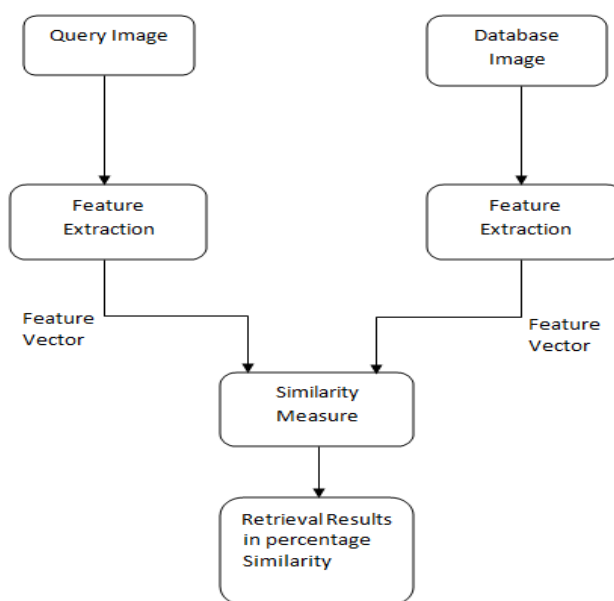


Fig1. Block diagram of basic CBIR system

## II. REVIEW OF LITERATURE

A survey on content based image retrieval is presented. Content Based Image Retrieval (CBIR) is a technique which uses visual features of image such as color, shape, texture, etc... to search user required image from large image database according to user's requests in the form of a query image. We consider Content Based Image Retrieval viz. labelled and unlabeled images for analyzing efficient image for different image retrieval process.

There are three fundamental bases for content based image retrieval, i.e. visual feature extraction, multidimensional indexing, and retrieval system design.

- Feature extraction and indexing of image database according to the chosen visual features, which from the

perceptual feature space, for example color, shape, texture or any combination of above.

- Feature extraction of query image.
- Matching the query image to the most similar images in the database according to some image-image similarity measure. This forms the search part of CBIR systems.

Feature extraction is the basis of content based image retrieval. Typically two types of visual feature in CBIR:

- Primitive features which include color, texture and shape.
- Domain specific which are application specific and may include, for example human faces and finger prints.

### III. FEATURE EXTRACTION TECHNIQUES

We have used the different methods to extract low-level features like color, texture & shape in Content based Image retrieval to obtain the desired results.

#### A. COLOR

Color is a powerful descriptor that simplifies object identification, and is one of the most frequently used visual features for content-based image retrieval. To extract the color features from the content of an image, a proper color space and an effective color descriptor have to be determined. The purpose of a color space is to facilitate the specification of colors. Each color in the color space is a single point represented in a coordinate system. Several color spaces, such as RGB, HSV and many more have been developed for different purposes [1]. Although there is no agreement on which color space is the best for CBIR, an appropriate color system is required to ensure perceptual uniformity. Therefore, the RGB color space, a widely used system for representing color images, is not suitable for CBIR because it is a perceptually non-uniform and device-dependent system [2]. The most commonly used method to represent color feature of an image is the color histogram.

##### a) Color Histogram

Color is the most widely used “feature” owing to its intuitiveness compared with other features and most importantly, it is easy to extract from the image. The color histogram depicts color distribution using a set of bins.

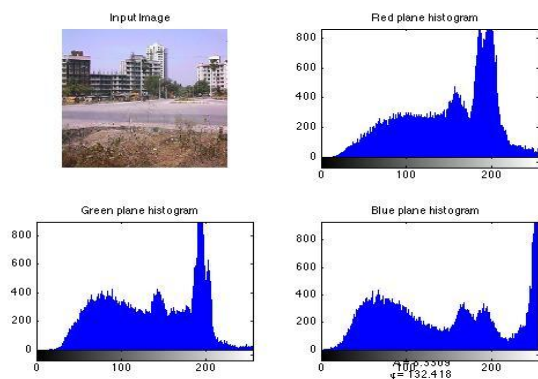


Fig2. Color histogram of an image

##### b) Color Moments

To overcome the quantization effects of the color histogram, we use the color moments as feature vectors for image

retrieval. Since any color distribution can be characterized by its moments and most information is concentrated on the low-order-moments, only the first moment (mean), the second moment (variance) and the third moment (skewness) are taken as the feature vectors.

$$E_i = \sum_{j=1}^N P_{ij} / N \tag{1}$$

$$\sigma_i = \sqrt{\sum_{j=1}^N (P_{ij} - E_i)^2 / N} \tag{2}$$

$$S_i = \sqrt[3]{\sum_{j=1}^N (P_{ij} - E_i)^3 / N} \tag{3}$$

#### B. TEXTURE

Texture is the innate property of all the surfaces and is easily perceptible to human beings. It contains the structural information about the surfaces and their relationship with the neighboring environment. Texture gives us information about the spatial arrangement of the colors or intensities in an image. This structural arrangement can classify the structures as rough, smooth, fine, irregular, lineated, etc [20].

Texture features in color photographs can be classified as (Haralick 1973) [20]:

- Spectral
- Structural
- Contextual

Spectral features describe the average tonal variations bands in the visible and/or the infrared region. Structural features define the spatial distribution of the tonal variations in the image whereas contextual features contain information derived from the blocks of pictorial data surrounding the area being analyzed [20].

##### a) Gray level co-occurrence matrix

Gray Level Co-occurrence Matrix is based on method is a way of extracting second order statistical texture features[3].

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element P(i, j | x,y) is the relative frequency with which two pixels, separated by a pixel distance (x,y), occur within a given neighborhood, one with intensity i and the other with intensity j. One may also say that the matrix element P (i, j | d, ) contains the second order statistical probability values for changes between gray levels i and j at a particular displacement distance d and at a particular angle[3]. The four properties calculated are:

- **Contrast** - The contrast property returns a measure of the intensity contrast between a pixel and its neighbor over the whole image [3].
- **Correlation** - Correlation measures the linear dependency of gray levels of neighboring pixels [3].
- **Energy** - Energy returns the sum of squared elements in the GLCM. This statistic is also called Uniformity or Angular second moment [16].
- **Homogeneity** - This statistic is also called as Inverse Difference Moment. In GLCM contrast and homogeneity

are strongly, but inversely, correlated in terms of equivalent distribution in the pixel pair population [16].

Table I

Feature	Formula
Energy	$\sum_i \sum_j P^2(i, j)$
Entropy	$\sum_i \sum_j P(i, j) \log P(i, j)$
Contrast	$\sum_i \sum_j (i - j)^2 P(i, j)$
Homogeneity	$\sum_i \sum_j \frac{P(i, j)}{1 +  i - j }$





Image	Gray Image	Energy	Contrast	Correlation	Homogeneity
		0.1235	0.3820	0.9420	0.8735
		0.0819	0.5867	0.9192	0.8332

Fig3. GLCM data

b) Gabor Filter Features

The Gabor filter has been widely used to extract image features, especially texture features. It is optimal in terms of minimizing the joint uncertainty in space and frequency, and is often used as an orientation and scale tunable edge and line (bar) detector [13]. There have been many approaches proposed to characterize textures of images based on Gabor filters. The basic idea of using Gabor filters to extract texture features is as follows.

A two dimensional Gabor function  $g(x, y)$  is defined as:

$$g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp \left[ -\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) + 2\pi j W x \right] \quad (4)$$

where,  $\sigma_x$  and  $\sigma_y$  are the standard deviations of the Gaussian envelopes along the x and y direction [13].

Then a set of Gabor filters can be obtained by appropriate dilations and rotations of  $g(x, y)$ :

$$g_{mn}(x, y) = a^{-m} g(x', y') \quad (5)$$

$$x' = a^{-m} (x \cos \theta + y \sin \theta) \quad (6)$$

$$y' = a^{-m} (-x \sin \theta + y \cos \theta) \quad (7)$$

where  $a > 1$ ,  $\theta = n\pi/K$ ,  $n = 0, 1, \dots, K-1$ , and  $m = 0, 1, \dots, S-1$ .  $K$  and  $S$  are the number of orientations and scales. The scale factor  $a^{-m}$  is to ensure that energy is independent of  $m$  [13].

Given an image  $I(x, y)$ , its Gabor transform is defined as:

$$W_{mn}(x, y) = \int I(x, y) g_{mn}^*(x - x_1, y - y_1) dx_1 dy_1$$

where \* indicates the complex conjugate

C. SHAPE

Shape is known as an important cue for human beings to identify and recognize the real-world objects, whose purpose

is to encode simple geometrical forms such as straight lines in different directions. Shape feature extraction techniques can be broadly classified into two groups. viz. contour based and region based methods. The former calculates shape features only from the boundary of the shape, while the latter method extracts features from the entire region. Each method has its own importance.

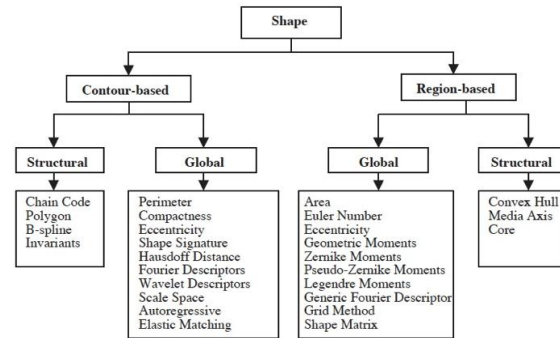


Fig4. Shape representation & extraction technique

a) Shape parameter

Shape-based image retrieval consists of the measuring of similarity between shapes represented by their features. Some simple geometric features can be used to describe shapes. They are usually used as filters to eliminate false hits or combined with other shape descriptors to discriminate shapes. These shape parameters are Area, Centroid, Eccentricity and the list goes on.

- **Area** - When the boundary points change along the shape boundary, the area of the triangle formed by two successive boundary points and the center of gravity also changes. This forms an area function, which can be exploited as shape representation. The area function is linear under affine transform. However, this linearity only works for shape sampled at its same vertices.
- **Centroid** - The center of gravity is also called centroid. Its position should be fixed in relation to the shape.
- **Eccentricity** - Eccentricity is the measure of aspect ratio. It is the ratio of the length of major axis to the length of minor axis. It can be calculated by principal axes method or minimum bounding rectangle method.



Image	Centroid	Area	Major Axis Length	Minor Axis Length	Eccentricity
	0.0256	2.0310	0.0290	0.0108	0.0001
	0.0256	2.7952	0.0312	0.0191	0.0001

Fig5. Shape Parameters

IV. DISTANCE SIMILARITY

One of the main tasks for (CBIR) systems is similarity

comparison, extracting feature vectors of every image based on its pixel values and defining rules for comparing images. These features become the image representation for measuring similarity with other images in the database. Distance metric or matching criteria is the main tool for retrieving similar images from large image databases for all the above categories of search. Several distance metrics, such as the L1 metric (Manhattan Distance), the L2 metric (Euclidean Distance) and the Vector Cosine Angle Distance (VCAD) have been proposed for measuring similarity between feature vectors [21]. In content-based image retrieval systems, Manhattan distance and Euclidean distance are typically used to determine similarities between a pair of images. In image processing applications, components of a feature vector (e.g., color histogram) are usually normalized by the size of the image and as a result, the Manhattan, Euclidean, the cosine angle based distance and Histogram Intersection distance metrics produce different ordering of retrieved images[21].

V. ALGORITHM

- Create a database.
- Read the Query input image.
- Calculate the query image features using color, shape and texture extraction techniques.
- The extraction methods used are Color Histogram, color Moments, region props, GLCM and Gabor feature extraction.
- Compute the features using the same techniques for Image database.
- Compare the difference between Query image feature and the features of the image database and calculate the Euclidean distance.
- Sort the Euclidean distance of the features of the image database.
- Retrieves the closest distance images from the image database.
- Calculate and display the percentage similarity of the retrieved images.
- Calculate Precision and Recall using following formulae

**Recall and Precision Calculation:**

Testing the effectiveness of the image search engine is about testing how well can the search engine retrieve similar images to the query image and how well the system prevents the return results that are not relevant to the source at all in the user point of view.

The first measure is called Recall. It is a measure of the ability of a system to present all relevant items [7]. The equation for calculating recall is given below:

**Recall**= (number of relevant items retrieved/number of relevant items in collection)

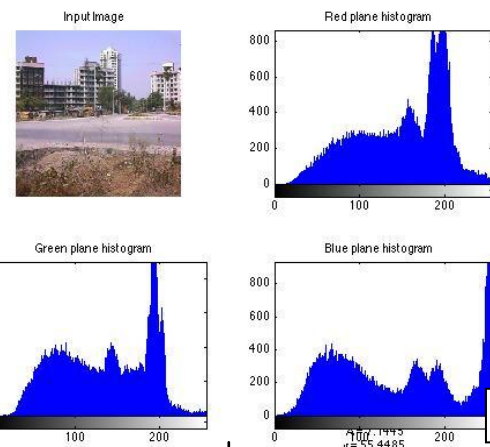
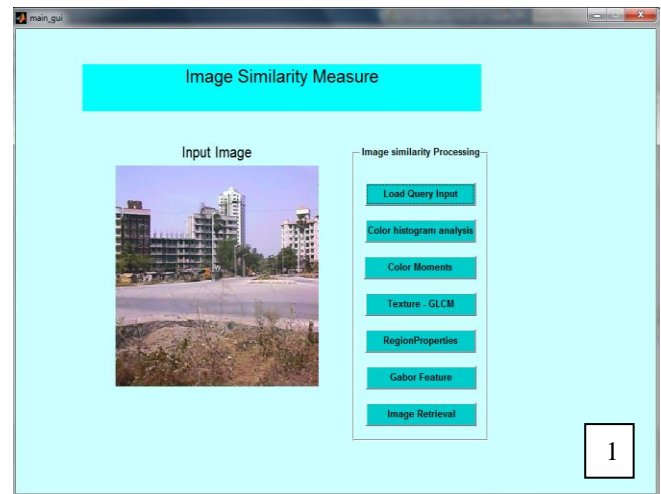
The second measure is called Precision. It is a measure of the ability of a system to present only relevant items [7]. The equation for calculating precision is given below.

**Precision**= (number of relevant items retrieved/total number of items retrieved)

The number of relevant items retrieved is the number of the returned images that are similar to the query image in this case. The number of relevant items in collection is the number of images that are in the same particular category with the

query image. The total number of items retrieved is the number of images that are returned by the search engine [7].

VI. RESULT



```

Command Window
color_hist =
    255
    255
    255

color_data =
    765

colorMoments =
    0 0 0 0 0 0

colorMoments =
    150.5581  51.5851  137.5161  53.2184  149.1284  75.5943

color_mom =
    617.6004

glcm =
    0.1152  0.8408  0.5901  0.9049
    
```



```

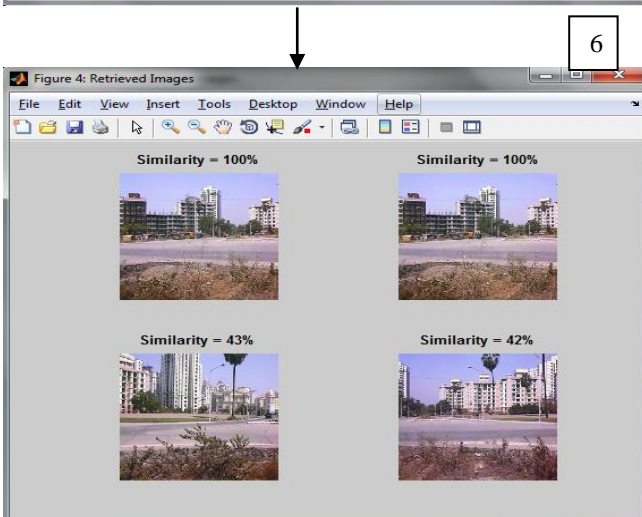
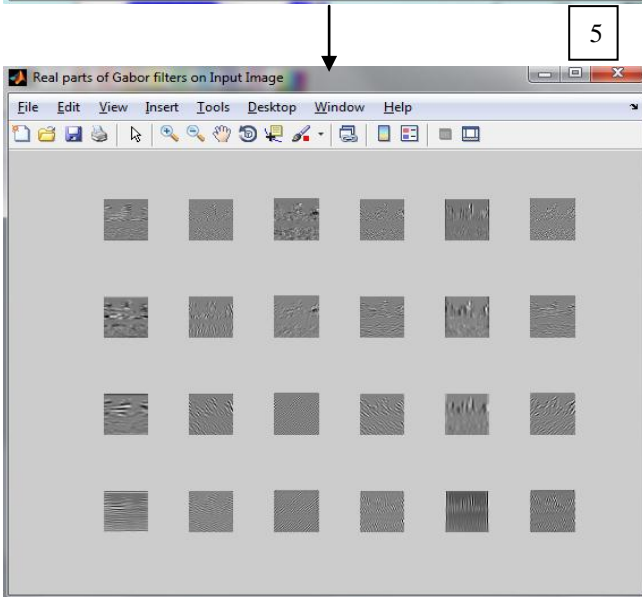
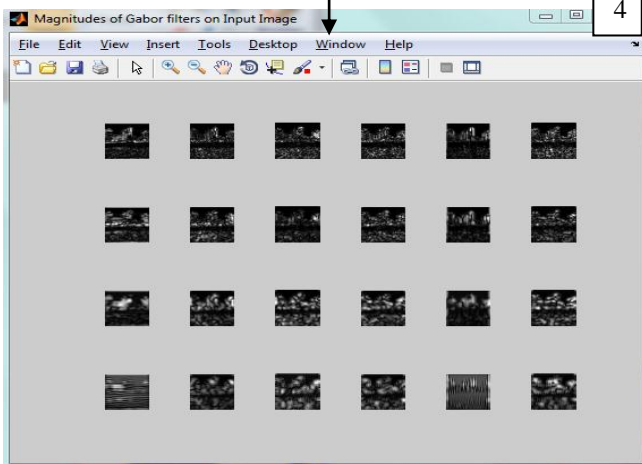
Command Window
glcm =
    0.1152    0.8408    0.5901    0.9049

glcm_fea =
    2.4511

regionprops =
    1.0e+04 *
    0.0256
    2.0310
    0.0290
    0.0108
    0.0001

region_data =
    2.0965e+04

gabor_fe =
    3.6181e-16
    
```



7

Database	Image
Recall	0.4
Precision(For Similarity Percentage >50)	0.5

Table: Recall and Precision

## VII. APPLICATIONS

- 1) The advantages of such systems range from simple users searching a particular image on the web.
- 2) Various types of professionals like police force for picture recognition in crime prevention.
- 3) Medicine diagnosis.
- 4) Architectural and engineering design.
- 5) Fashion and publishing.
- 6) Geographical information and remote sensing systems.
- 7) Home entertainment

## VIII. CONCLUSION

The explosive growth of image data leads to the need of research and development of Image Retrieval. Content-based image retrieval is currently a very important area of research in the area of multimedia databases. Plenty of research works had been undertaken in the past decade to design efficient image retrieval techniques from the image or multimedia databases. More précised retrieval techniques are needed to access the large image archives being generated, for finding relatively similar images. This paper has presented a brief overview of content-based image retrieval area. This paper investigated the use of a number of different color, texture and shape features for image retrieval in CBIR. In this work the color histogram, color Moments, region properties, GLCM, and Gabor filter feature extraction techniques are used to design efficient content based image retrieval. The experiment also shows that only color features or only texture features or only shape features are not sufficient to describe an image. There is considerable increase in retrieval efficiency when shape, color and texture features are combined. We have achieved precision of and recall on the database we have used.

## ACKNOWLEDGMENT

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