

Color Based Image Retrieval Using Texture Features and Image Mining Techniques

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Abstract: Increasing use of World Wide Web and communication channels like mobile networking has increased the number of images used throughout the world. As processors become increasingly powerful, and memories become increasingly cheaper, the deployment of large image databases for a variety of applications have now become realisable. Databases of art works, satellite and medical imagery have been attracting more and more users in various professional fields — for example, geography, medicine, architecture, advertising, design, fashion, and publishing. Effectively and efficiently accessing desired images from large and varied image databases is now a necessity. Image mining is an extended branch of data mining that is concerned with the process of knowledge discovery concerning digital images. Image retrieval is the basic requirement task in the present scenario. Color Based Image Retrieval (CBIR) is the popular image retrieval system by which the target image to be retrieved based on the useful features of the given image. The concepts of CBIR and Image mining combined to increase the speed of the image retrieval system.

Keywords: Image mining, color based image retrieval (CBIR), GLCM, texture.

1. Introduction

Interest in the digital images has increased enormously over the last few years, image data is the major one and large amount of images being generated in daily life such as business for marketing, hospital for surgery, crime prevention, medical diagnosis, journalists need photographs of particular type of event, designers looking for materials with a particular color or texture, and engineers looking for drawings of a particular type of part, all need some form of access by image content. The main problem highlighted was difficulty of locating a desired image in a large and varied collection. While it is perfectly easy to identify a desired image from a small collection images simply by browsing, large volume of images makes difficult for user to browse through entire database.

The need for efficient storage and retrieval of images recognized by users of large image collections. Image retrieval is concerned with techniques for storing and retrieving images both efficiently and effectively. It is fast growing and challenging area. Two different types of approaches in image retrieval are Text based image retrieval and Content based image retrieval.

Text based image retrieval system only concern about text described by humans, instead of looking into the content of images. Images become a replica of what human has seen since birth. In this approach, human first manually describe each image using keywords. Then images are retrieved based on keywords in the text description. However, for the relevant search results, there could be a large amount of irrelevant search results. In many situations, a few words cannot describe the image content and many words have multiple meanings. For example, the query term sun may retrieve photos of sun or the logos of sun Microsystems Company. Here, the definition of relevancy depends on interest of the user and may soon lose patience flipping through dozens of pages of images that contain many irrelevant images.

Text based image retrieval is very efficient for simple and small image databases, since just few hundreds of keywords can describe the whole database. The memory and storage made the size of image databases grow considerably. As the image databases and image size grow, there will be more images having different contents and the images having rich contents cannot be described by only few keywords. The demand of labour on annotating the images has raised and searching a large image database by means of keywords are time consuming and inefficient. To overcome the drawbacks of text based image retrieval, content based image retrieval is introduced.

2. Image Mining Techniques

Image mining is the extraction of implicit knowledge, image data relationship. The focus of image mining is in the extraction of patterns; derive knowledge from large collections of images.

2.1 Object recognition

An object recognition system finds objects in the real world from an image, Using object models that are known a priori. Automatic machine learning and meaningful information extraction can only be realized when some objects have been identified and recognized by the machine. The object recognition problem can be referred to as a supervised labelling problem based on models of known objects. That is, given a target image containing one or more interesting objects and a set of labels corresponding to a set of models known to the system, what object recognition does is to assign correct labels to regions, or a set of regions, in the image. Models of known objects are usually provided by human input a priori.

An object recognition system typically consists of four components, namely, model database, feature detector, hypothesizer and hypothesis verifier. The model database contains all the models known to the system. The

information in the model database depends on the approach used for the recognition.. A feature is some attribute of the object that is considered important in describing and recognizing the object in relation to other objects. Size, color, and shape, texture are some commonly used features.

The feature detector applies operators to images and identifies locations of features that help in forming object hypotheses. The features used by a system depend on the types of objects to be recognized and the organization of the model database. Using the detected features in the image, the hypothesizer assigns likelihoods to objects present in the scene. This step is used to reduce the search space for the recognizer using certain features. The model base is organized using some type of indexing scheme to facilitate elimination of unlikely object candidates from possible consideration. The verifier then uses object models to verify the hypotheses and refines the likelihood of objects. The system then selects the object with the highest likelihood, based on all the evidence, as the correct object.

2.2 Image Classification and clustering

The basic idea in classification is to recognize objects based on features. class assume that N features have been detected in images. Suppose that a feature values for each class is known and is represented for class i as f_{ij} , $j = 1, \dots, N$, $i = 1, \dots, M$ where M is the number of object classes. Now suppose that we detect and measure features of the unknown object U and represent them as u_{ij} , $j = 1, \dots, N$.

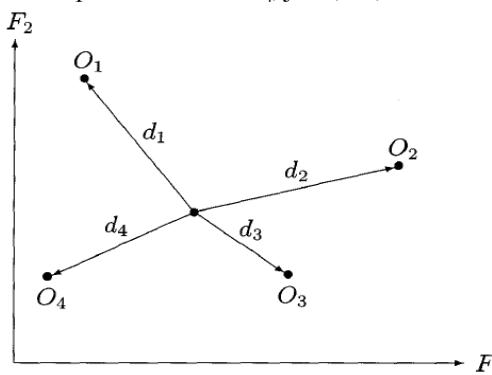


Figure 1: An unknown object is assigned to the closest class by using a distance measure

To decide the class of the object, we measure its similarity with each class by computing its distance from the points representing each class in the feature space and assign it to the nearest class.. In general, we compute the distance d_j of the unknown object from class j as given by

$$\sum_{j=1}^n (u_{ij} - f_{ij})^2$$

The distance to a class was computed by considering distance to the feature point representing a object. Many objects may be known to belong to a class. In this case, one must consider feature values for all known objects of a class.

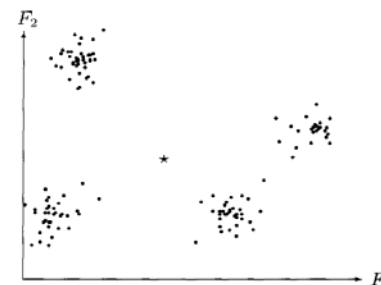


Figure 2: All known objects of each class are represented as points in the feature space. Each class is thus represented by a cluster of points

2.3 Image Retrieval

Image mining requires that images be retrieved according to some requirement specifications. The requirement specifications can be classified into three levels:

- Level 1 comprises image retrieval by primitive features .The queries include “Retrieve the images with long thin red objects in the top right-hand corner” and “Retrieve the images containing blue stars arranged in a ring”.
- Level 2 comprises image retrieval by derived or logical features like objects of a given type or individual objects or persons. These queries include “Retrieve images of round table” and “Retrieve images of Jimmy”.
- Level 3 comprises image retrieval by abstract attributes, involving a significant amount of high level reasoning about the meaning or purpose of the objects or scenes depicted. For example, we can have queries such as “Retrieve the images of football match”

The basic idea in Query by Description is that by storing description along with each image through which the user can locate the images interested. The image description is often called label or keyword. This description is typically generated manually and assigned to each image in the image pre processing stage. Ideally, the description should be discriminative, concrete and unambiguous. In a practice, this approach suffers from the drawbacks of the “vocabulary problem”.

3. Color Based Image Retrieval 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. system operates in four phases.

- a) **Querying:** The user provides a sample image as the query for the system.
- b) **Feature Extraction:** Extract visual features for user query image and database images.
- c) **Similarity Computation:** The system computes 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,

$$\text{Euclidian distance} = \sqrt{\sum_{i=1}^n (D_i - Q_i)^2}$$

Where, D_i and Q_i are the feature vectors of image D and query image Q respectively.

d) **Retrieval:** Each image that is stored in the database has its features extracted and compared to the features of query.

3.1 Pre-processing

Pre-processing is done on images at the lowest level of abstraction. The aim of the pre-processing is to suppress unwilling distortions and enhance some image features, which is important for future processing of the images. This step focuses on image feature processing.

3.2 Contrast Enhancement

Steps for contrast enhancement

- Load image
- Resize image
- Enhance grayscale image

4. Texture Analysis

Texture is a feature that can help to segment images into regions of interest and to classify those regions. The image of Figure 3 has three very distinct textures: the texture of the tiger, the texture of the jungle, and the texture of the water. These textures can be quantified and used to identify the object classes they represent.



Figure 3: An image containing several different regions, each having a distinct texture

Texture gives us information about the spatial arrangement of the colors or intensities in an image. Suppose that the histogram of a region tells us that it has fifty percent white pixels and fifty percent black pixels. Figure 2 shows three different images of regions with this intensity distribution that would be considered three different textures. The leftmost image has two big blocks: one white and one black. The centre image has 18 small white blocks and 18 small black blocks forming a checkerboard pattern. The rightmost image has six long blocks, three white and three black, in a striped pattern.

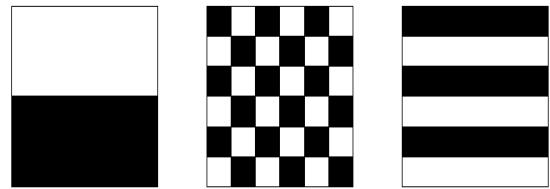


Figure 4: Three different textures with the same distribution of black and white.

The images of Figure 4 were artificially created and contain geometric patterns constructed from black and white rectangles. Texture is commonly found in natural scenes, particularly in outdoor scenes containing both natural and man-made objects. Sand, stones, grass, leaves, bricks, and many more objects create a textured appearance in images. Figure 3 illustrates some of these natural textures. Note that the two different brick textures and two different leaf textures shown are quite different.

The textures of Figure 4 are made up of primitive rectangular regions in white or black. In the checkerboard, the regions are small squares arranged in a 2D grid of alternating colors. In the striped pattern, the regions are long stripes arranged in a vertical sequence of alternating colors. It is easy to segment out these single color regions and to recognize these simple patterns.

Now, consider the two leaf textures of Figure 5. The first has a large number of small, round leaves, while the second has a smaller number of larger, pointed leaves. It is difficult to describe the spatial arrangements of the leaves in words; the arrangements are not regular, but there is some quality of the image that would make one argue that there is a noticeable arrangement in each image.

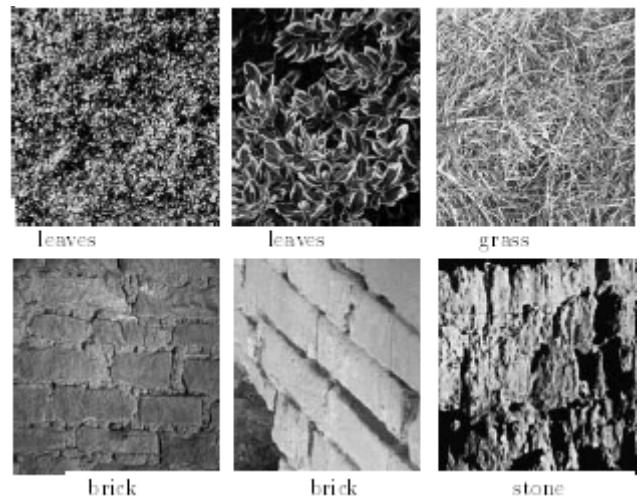


Figure 5: Natural textures

Texture, the pattern of information or arrangement of the structure found in an image, is an important feature of many image types. In a general sense, texture refers to surface characteristics and appearance of an object given by the size, shape, density, arrangement, proportion of its elementary parts. Due to the significance of texture information, texture feature extraction is a key function in various image processing applications, remote sensing and content based image retrieval.

4.1 Gray level co occurrence matrix

Second-order statistics are defined as the likelihood of observing a pair of gray values occurring at the endpoints of a dipole (or needle) of random length placed in the image at a random location and orientation. GLCM directions of analysis:-Horizontal (0 or 180°), Vertical (90 or 270), Right Diagonal (45 or 225), Left diagonal (135 or 315°). Denoted as P_0 , P_{45} , P_{90} , & P_{135} respectively. Fig.1 shows directional analysis of $P(0^\circ)$, $P(45^\circ)$, $P(90^\circ)$, $P(135^\circ)$ in an image. If the adjacent pixel to the pixel of interest is along x axis then it referred to as 0° directional analysis. If the adjacent pixel to the pixel of interest is along 45° then it referred to as 45° directional analysis. If the adjacent pixel to the pixel of interest is along 90° then it referred to as 90° directional analysis. If the adjacent pixel to the pixel of interest is along 135° then it referred to as 135° directional analysis. For each direction GLCM can be calculated. We can obtain four different GLCM for a same image or image sub-region. classifier. Then we need to extract features from it. For this, hear features shown in below image are used. They are just like our convolutional kernel. Each feature is a single value obtained by subtracting sum of pixels under white rectangle from sum of pixels under black rectangle.

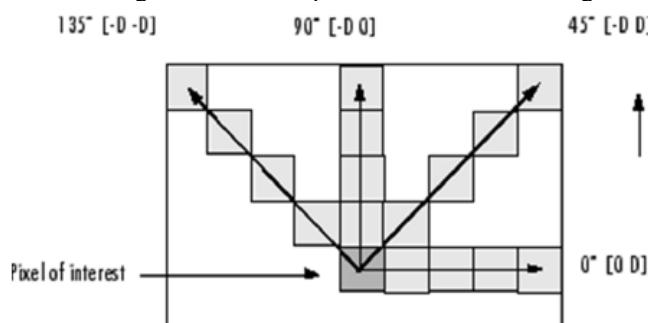


Figure 6: Directional analysis

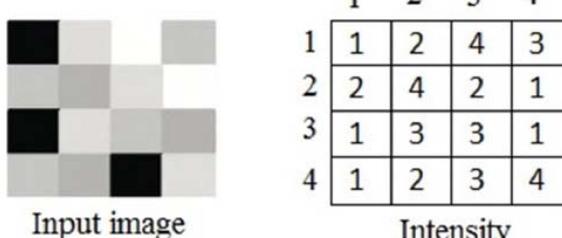


Figure 7: Input image and its corresponding intensity levels

1	2	3	4	5
1	0	3	1	0
2	3	0	1	3
3	1	1	1	2
4	0	3	2	0
5	0	0	1	0

$P(0^\circ)$

Figure 8: GLCM for 0°

1	2	3	4	5
1	1	1	1	1
2	1	0	2	2
3	1	2	1	1
4	1	2	1	0
5	1	1	0	0

$P(45^\circ)$

Figure 9: GLCM for 45°

1	2	3	4	5
1	0	0	3	0
2	0	1	3	0
3	3	3	0	0
4	0	0	0	1
5	0	0	0	1

$P(90^\circ)$

Figure 10: GLCM for 90°

1	2	3	4	5
1	0	1	0	2
2	1	1	1	0
3	0	1	1	2
4	2	0	2	0
5	0	1	0	0

$P(135^\circ)$

Figure 11: GLCM for 135°

Haralick has extracted many properties or features from GLCM. To extract Haralick features GLCM should be a symmetric and normalized matrix. To make a matrix symmetric, we should take transpose of GLCM and add it with the original GLCM. To get a normalized matrix, calculate sum of all elements in a GLCM and divide each element of the matrix with the obtained sum. From the normalized symmetrical GLCM texture features are extracted. The properties or features extracted from normalized symmetrical GLCM are;

- Energy or Angular second moment
- Correlation.
- Homogeneity.
- Contrast.

5. Results

Using the colour based image retrieval method described above, where the features of the query image and the images in the database are compared using the Euclidean distance formula. The following results are obtained.



Figure 12: The query image

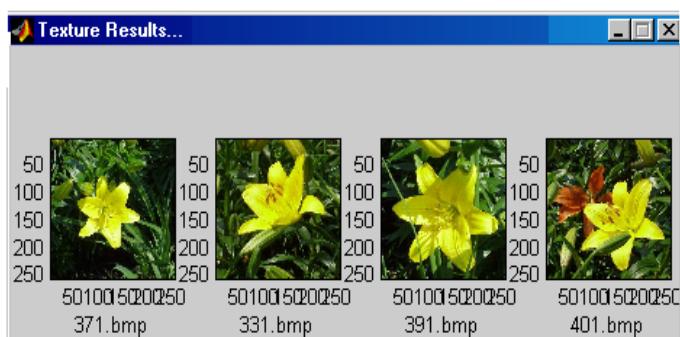


Figure 13: The retrieved images

6. Conclusion

The dramatic rise in the sizes of images databases has stirred the development of effective and efficient retrieval systems. The development of these systems started with retrieving images using textual connotations but later introduced image retrieval based on content. This came to be known as CBIR or Content Based Image Retrieval. Systems using CBIR retrieve images based on visual features such as colour, texture and shape.

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