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CONTENT BASED IMAGE RETRIEVAL SYSTEM

DANDGE S.S. AND BODKHE A.P.

Department of Information Technology, Prof. Ram Meghe Institute Of Technology and Research, Badnera, MS, India.
*Corresponding Author: Email- sangramdandge@gmail.com, dandgesangram@rediffmail.com

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Abstract- The field of image retrieval has been an active research area for several decades and has been paid more and more attention in recent years as a result of the dramatic and fast increase in the volume of digital images. The developments of Internet not only cause an explosively growing volume of digital images, but also give people more ways to get those images. So, for this propose content based image retrieval system. Is a technique for retrieving images on the basis of derived features such as color, texture and shape. It will be helpful and easy way to retrieve image from huge database. In order to find image from huge database which uses dominant color it is image is uniformly divide into 8 coarse partition as a first step after above coarse partition, the centroid of each partition is selected dominant color .Texture of an image of an image is obtain by gray level Co-Occurrence matrix (GLCM) and as per shape concern we propose partial shape matching. Thus, using matching and comparison algorithms, the color, texture and shape features of one image are compared and matched to the corresponding features of another image. This comparison is performed using color, texture and shape distance metrics. In the end, these metrics are performed one after another, so as to retrieve database images that are similar to the query .
Keywords- Digitalize ,feature extraction, image feature database, image database, image matching and multidimansial indexing.

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Introduction

The importance of an effective technique in searching and retrieving images from huge data base, for this proposed Content base image retrieval (CBIR) System[1].

Content Based Image Retrieval is the retrieval of images based on visual features such as color, texture and shape. Reasons for its development are that in many large image databases, traditional methods of image indexing have proven to be insufficient, laborious, and extremely time consuming. These old methods of image indexing, ranging from storing an image in the database and associating it with a keyword or number, to associating it with a categorized description, have become obsolete. This is not in CBIR. In CBIR, each image that is stored in the database has its features extracted and compared to the features of the query image. It involves two steps[2]:

Feature Extraction

The first step in the process is extracting image features to a distinguishable extent.

Matching

The second step involves matching these features to yield a result that is visually similar.

Existing System

Early techniques were not generally based on visual features but on the textual annotation of images. In other words, images were first annotated with text and then searched using a text-based approach from traditional database management systems. Text-based image retrieval uses traditional database techniques to manage images. Through text descriptions, images can be organized by topical or semantic hierarchies to facilitate easy navigation and browsing based on standard Boolean queries. However, since automatically generating descriptive texts for a wide spectrum of images is not feasible, most text-based image retrieval systems require manual annotation of images. Obviously, annotating images manually is a cumbersome and expensive task for large image databases, and is often subjective, context-sensitive and incomplete. As a result, it is difficult for the traditional text-based methods to support a variety of task-dependent queries [3,4].

Proposed System

The proposed system is to extract the visual features of a query image and compare them to those of database images. The image features under consideration were color, texture and shape. Thus, using matching and comparison algorithms, the color, texture and shape features of one image are compared and matched to the corresponding features of another image. This comparison is performed using color, texture and shape distance metrics. In the end, these metrics are performed one after another, so as to retrieve database images that are similar to the query[5].

Objective and Scope

Some of the most important objective can be:

- Understanding image user's needs and information-seeking behavior.
- Identification of suitable ways of describing image content.
- Extracting visual features from raw images.
- Providing compact storage for large image databases.
- Matching query and stored images in a way that reflects human similarity judgments.
- Efficiently accessing stored images by content.
- Providing usable human interfaces to CBIR systems.

A wide range of possible scope for Content Base Image Retrieval technology has been identified. Potentially fruitful areas include: Crime prevention, the military, Fashion and interior design, Journalism and advertising, Medical diagnosis, Geographical information and remote sensing systems, Web searching[6].

General Schema diagram of Content Based image Retrieval

The block diagram consists of following main blocks - digitizer, feature extraction, image database, feature database, and matching and multidimensional indexing. Function of each block is as follows

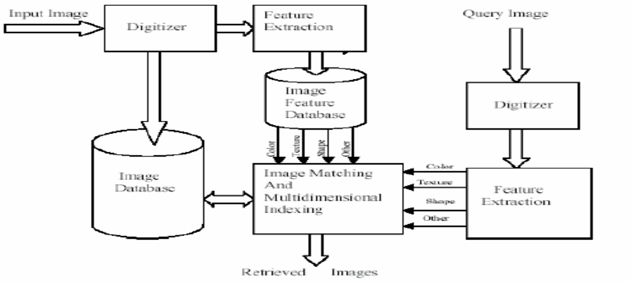


Fig. 1- General schema of Content Based image Retrieval

Digitizer- To add new images in image database or query images which are acquired from Cameras, X-ray imaging system, microdensitometer's, image dissectors, vision cameras etc. are needed to be digitized, so that computer can process those images.

Image Database- The Comparison between Query image and images from image database can be done directly pixel by pixel which will give precise match but on the other hand, recognizing objects entirely at query time will limit the retrieval speed of the system, due to the high expense of such computing. Generally this crude method of comparison is not used, but image database, which contains raw images, is required for visual display purpose.

Feature Extraction- To avoid above problem of pixel-by-pixel comparison next abstraction level for representing images is the feature level. Every image is characterized by a set of features such as Texture, Color, Shape and others. Extract these features at the time of injecting new image in image database. Then summarize these features in a reduced set of k indexes and store it in Image feature database. The query image is processed in the same way as images in the database. Matching is carried out on the feature database.

Image matching and Multidimensional Indexing- Extracted features of query image are compared with features, which are stored in image feature database. To achieve fast retrieval speed and make the retrieval system truly scalable to large size image collections and effective multidimensional indexing is indispensable part of the whole system. The system selects the N images having the greatest overall similarities[7,8].

Proposed Algorithim in CBIR System

To describe image from the different aspects in order to obtain better search results and to express more image information, we consider the dominant color, texture and shape features combined. The proposed method is based on dominant color, texture and shape features of image.

The retrieval steps can be as follows:

1. Uniformly divide each image in the database and the query image into 8-coarse partitions.
2. For each partition, the centroid of each partition can be selected as its dominant color.
3. Obtain texture features.
4. Obtain shape features.
5. Construct a combined feature vector for color, texture and shape.
6. Find the distances between feature vector of query image and the feature vectors of target images.
7. Sort the distances.
8. Retrieve most similar images with minimum distance.

Visual features

Feature extraction plays an important role in content-based image retrieval to support for efficient and fast retrieval of similar images from image databases. Significant features must first be extracted from image data. Retrieving images by their content, as opposed to external features, has become an important operation. A fundamental ingredient for content based image retrieval is the technique used for comparing images. There are two general methods for image Comparison: intensity based (color and texture) and geometry based (shape). So we will concentrate on this feature.

Color

One of the most important features that make possible the recognition of images by humans is color. Color is a property that depends on the reflection of light to the eye and the processing of that information in the brain. We use color everyday to tell the difference between objects, places, and the time of day. Usually colors are defined in three dimensional color spaces. These could either be *RGB* (Red, Green, and Blue), *HSV* (Hue, Saturation, and Value) or *HSB* (Hue, Saturation, and Brightness). The last two are dependent on the human perception of hue, saturation, and brightness. Most image formats such as *JPEG*, *BMP*, *GIF*, use the RGB color space to store information. The RGB color space is defined as a unit cube with red, green, and blue axes. Thus, a vector with three co-ordinates represents the color in this space. When all three coordinates are set to zero the color perceived is black. When all three coordinates are set to one the color perceived is white. The other color spaces operate in a similar fashion but with a different perception[1].

Color is one of the most widely used low-level visual features and is invariant to image size and orientation. As conventional color features used in CBIR, there are color histogram, color correlogram, and dominant color descriptor (DCD).Color histogram is the most commonly used color representation, but it does not include any spatial information. Color correlogram describes the probability of finding color pairs at a fixed pixel distance and provides spatial information. Therefore color correlogram yields better retrieval accuracy in comparison to color histogram. Color autocorrelogram is a subset of color correlogram, which captures the spatial correlation between identical colors only. Since it provides significant computational benefits over color correlogram, it is more suitable for image retrieval. DCD is MPEG-7 color descriptors [4]. DCD describes the salient color distributions in an image or a region of interest, and provides an effective ,compact, and intuitive representation of colors presented in an image. However, DCD similarity matching does not fit human perception very well, and it will cause incorrect ranks for images with similar color distribution In Yang et al. presented a color quantization method for dominant color extraction, called the linear block algorithm (LBA), and it has been shown that LBA is efficient in color quantization and computation. For the purpose of effectively retrieving more similar images from the digital image databases (DBs), Lu et al. uses the color distributions, the mean value and the standard deviation, to represent the global characteristics of the image, and the image bitmap is used to represent the local characteristics of the image for increasing the accuracy of the retrieval system[7,11].

Feature Extraction of dominant color of an image

The procedure to extract dominant color of an image is as follows:
According to numerous experiments, the selection of color space is not a critical issue for DCD extraction. Therefore, for simplicity and without loss of generality, the RGB color space is used. Firstly, the RGB color space is uniformly divided into 8 coarse partitions, as shown in Fig.2..If there are several colors located on the same partitioned block, they are assumed to be similar. After the above coarse partition, the centroid of each partition is selected as its quantized color. Let X=(XR, XG,XB) represent color components of a pixel with color components Red, Green, and Blue, and Ci be the quantized color for partition i.[12,13].

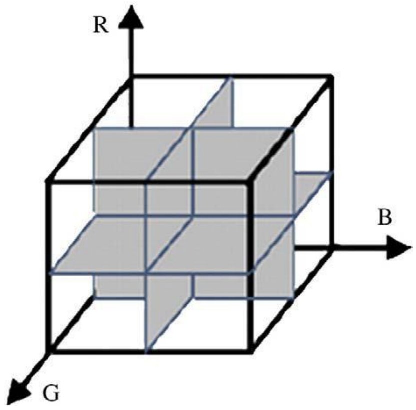


Fig. 2- The coarse division of RGB color space

The average value of color distribution for each partition center can be calculated by

$$\overline{X}_i = \frac{\sum_{x \in C_i} x}{\sum_{x \in C_i} 1}$$

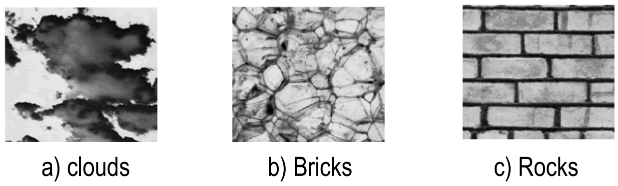
After the average values are obtained, each quantized color can be determined by using

$$C_i = \left(\overline{X}_i^R, \overline{X}_i^G, \overline{X}_i^B\right) (1 \le i \le 8)$$

In this way, the dominant colors of an image will be obtained.

Texture

Texture is that innate property of all surfaces that describes visual patterns, each having properties of homogeneity. It contains important information about the structural arrangement of the surface, such as; clouds, leaves, bricks, fabric, etc. It also describes the relationship of the surface to the surrounding environment .In short; it is a feature that describes the distinctive physical composition of a surface. Texture properties include: (i) Coarseness, ii) Contrast, iii) Directionality, iv) Line-likeness, v) Regularity & v) Roughness[13,16].



a) clouds b) Bricks c) Rocks

Fig. 3- Examples of Textures

Feature Extraction of Texture of an image

Most natural surfaces exhibit texture, which is an important low level visual feature. Texture recognition will therefore be a natural part of many computer vision systems. In this paper, we propose a texture representation for image retrieval based on GLCM. GLCM is created in four directions with the distance between pixels as one. Texture features are extracted from the statistics of this matrix. Four GLCM texture features are commonly used which are given below:

GLCM is composed of the probability value, it is defined by $P(i, j|d,\theta)$ which expresses the probability of the couple pixels at θ direction and d interval. When θ and d is determined by $P(i, j|d,\theta)$ is showed by Pi, j. Distinctly GLCM is a symmetry matrix and its level is determined by the image gray-level. Elements in the matrix are computed by the equation shown below:[8,9].

$$P(i,j|d,\theta)=\frac{P(i,j|d,\theta)}{\sum_i \sum_j P(i,j|d,\theta)}$$

GLCM expresses the texture feature according the correlation of the couple pixels gray-level value at different positions. It quantificational describes the texture feature. In this paper, four texture features are considered. They include energy, contrast, entropy, inverse difference.

Energy $E=\sum_x \sum_y P(x,y)^2$

It is a texture measure of gray-scale image represents homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture.

Contrast $I = \sum\sum(x-y)\ P(x,y)$

Contrast is the main diagonal near the moment of inertia, which measures how the values of the matrix are distributed and number of images of local changes reflecting the image clarity and texture of shadow depth. Large Contrast represents deeper texture

Entropy $S= - \sum\sum P(x,y)\log p(x,y)$

Entropy measures randomness in the image texture. Entropy is minimum when the co-occurrence matrix for all values is equal. On the other hand, if the value of co-occurrence matrix is very uneven, its value is greater. Therefore, the maximum entropy implied by the image gray distribution is random.

Inverse difference $H= \sum_x \sum_y \frac{1}{1+(x+y)} P(x,y)$

It measures number of local changes in image texture. Its value in large is illustrated that image texture between the different regions of the lack of change and partial very evenly. Here p(x, y) is the gray-level value at the Coordinate (x, y). The texture features are computed for an image when d=1 and $=0^0, 45^0, 90^0, 135^0$. In each direction four texture features are calculated. They are used as texture feature descriptor. Combined feature vector of Color and texture is formulated**.**

Shape

This seminar discusses the Partial shape matching for scale invariant and deformation tolerant images. Shape matching is a fundamental problem in computer vision and pattern recognition. Scale invariance is a feature of objects or laws that do not change if scales of length, energy, or other variables, are multiplied by a common factor. Deformation tolerance means tolerating a change in the volume and/or shape of object[24]. The main idea is to develop a computationally inexpensive and transformation invariant measure of a shape boundary that can be used in shape recognition. Shape is an important cue as it captures a prominent element of an object. Shape matching amounts to developing computational methods for comparing shapes that agree as much as possible with the human notion of shape similarity. Shapes are represented as binary images depicting foreground objects over their background and developing a shape descriptor for a sampled boundary point of any shape[20,21].

The matching method we propose operates on 2D images. Shapes are represented as binary images depicting foreground objects over their background. We assume that the shapes have already been extracted from images and are represented by their bounding contours. The basic idea behind our approach is to represent each shape by a sequence of convex and concave segments and to allow the matching of merged sequences of small segments in a noisy shape with larger segments in the other shape. A variety of shape matching algorithms are available to address the 2D shape matching problem such as, Smith Waterman Algorithm, algorithm, Dynamic alignment matching algorithm, genetic algorithm etc.[22,23].

Conclusion

The image retrieval system started with retrieving images using textual annotations but later introduced image retrieval based on content this came to be known as Content Based Image Retrieval System. Using this proposed design images based on visual features such as color, texture, shape, as opposed to depending on image descriptions or textual indexing can be retrieved. In this seminar is proposed an image is stored in the database has its features extracted and compared to the features of the query image by using Extraction and matching.

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