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ORIGINAL ARTICLE

CONTENT BASED IMAGE RETRIEVAL OF IMAGE USING WAVELET TRANSFORM

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Abstract:

Abstract -Retrieval of a query image from a large database of images is an important task in the area of computer vision and image processing. A number of good search engines are available today for retrieving the image, but there are not many fast tools to retrieve intensity and color images. Thus there is continued need to develop efficient algorithms in image mining and content based image retrieval and resizing.

In content based image retrieval system (CBIR) systems, the images are searched and retrieved based on the visual content of the images. In the first part of CBIR system, the images from the image database are processed offline. The features from each image in the image database are extracted to form the metadata information of the image, in order to describe the image using its visual content features. Next these features are used to index the image, and they are stored into the metadata database along with the images. In the second part, the retrieval process is depicted. The query image is analyzed to extract the visual features, and these features are used to retrieve the similar images from the image database.

Rather than directly comparing two images, similarity of the visual features of the query image is measured with the features of each image stored in the metadata database as their signatures. The retrieval systems returns the most matching image.

KEYWORDS:

Wavelet, CBIR , Image .

INTRODUCTION:

Retrieval of a query image from a large database of images is an important task in the area of computer vision and image processing. The advent of large multimedia collection and digital libraries has led to an important requirement for development of search tools for indexing and retrieving information from them. A number of good search engines are available today for retrieving the text in machine readable form, but there are not many fast tools to retrieve intensity and color images. The traditional approaches for searching and indexing images are slow and expensive. Thus there is continued need to develop efficient algorithms in image mining and CBIR.

Tremendous amount of visual information in the form of image and video data are distributed all over the world like any other nonvisual data such as numeric and nonnumeric data, speech, voice, text, etc. Data mining is the field of study to extract valuable information from very large data set by discovering patterns and knowledge embedded into the data. Image mining broadly deals with extraction of the valuable information embedded in large image and video databases. This promising field is still in the early stage of its development. Most of the work in this area has been restricted mainly in the development of content-based image retrieval (CBIR) systems. Retrieval of a query image from a large database of images is an important task in the area of computer vision and image processing. The advent of large multimedia collection and digital libraries has led to an important requirement for development of search tools for indexing and retrieving information from them. A number of good search engines are available today for retrieving the text in machine readable form, but there are not many fast tools to retrieve intensity and color images. The traditional approaches for searching and indexing images are slow and expensive.Thus there is continued need to develop efficient algorithms in image mining and CBIR. The indexing and retrieval of images usually seeks to find semantic information. Retrieving this semantic information and automatic segmentation of the image into objects using machine vision techniques is a nontrivial problem today. Many image attributes such as color, shape are having direct correlation with semantics embedded in the image. Image retrieval using similarity measures is an elegant technique used in content-bused image retrieval (CBIR). Ideally a CBIR system should automatically extract the semantic information about the images for a specific application area. To a very large extent, the low-level image features such as color, texture, and shape are widely used for CBIR. While attempting the task of image retrieval, we identify the mutual correspondence between two images in a set of database images using similarity relations. The content-based query system processes a query image and assigns this unknown image to the closest possible image available in the database

II RELATED WORK

An image may have one or more major regions. For image identification and retrieval, we need to segment the regions from the background before we can accurately describe image.Image segmentation is necessary step to achieve this. However, it is very difficult to achieve perfect segmentation in most gray-scale and color images. Due to their importance, many color image segmentation algorithms had been proposed in the past few decades.

The architecture for a possible content-based image retrieval system is shown in Figure 1. The CBIR systems architecture is essentially divided into two parts. In the first part, the images from the image database are processed offline. The features from each image in the image database are extracted to form the metadata information of the image, in order to describe the image using its visual content features. Next these features are used to index the image, and they are stored into the metadata database along with the images. In the second part, the retrieval process is depicted. The query image is analyzed to extract the visual features, and these features are used to retrieve the similar images from the image database. Rather than directly comparing two images, similarity of the visual features of the query image is measured with the features of each image stored in the metadata database as their signatures. Often the similarity of two images is measured by computing the distance between the feature vectors of the two images. The retrieval systems return the first k images, whose distance from the query image is below some defined threshold. Several image features have been used to index images for content-based image retrieval systems. Most popular among them are color, texture, shape, image topology, color layout, region of interest, etc.

A. Image Region Extraction

Background regions are usually visible along the periphery of the image.The pixels corresponding to different regions are normally clustered spatially and have a certain shape. Each pixel of the image can be represented as a point in 3-D color space. Commonly used color spaces for image retrieval include RGB, Munsell, CIE L*a*b*, CIEL*u*v*, HSV (or HSL HSB), and the opponent color space. It is Difficult to determine which color space is the best for tackling the problem. However, one of the desirable characteristics of an appropriate color space for image retrieval is its perceptual uniformity. Perceptual uniformity means that two colors that have the same similarity distance to the same reference color in a color space are perceived as equal by viewers. In other words, the measured Proximity among colors must be directly related to the psychological similarity among them. We select the RGB color space, RGB color space is the most used color space for computer graphics. Note that R, G, and B stand here for intensities of the Red, Green, & Blue guns in a CRT, not for primaries as meant in the CIE RGB space. It is an additive color space: red, green, and blue light are combined to create other colors.

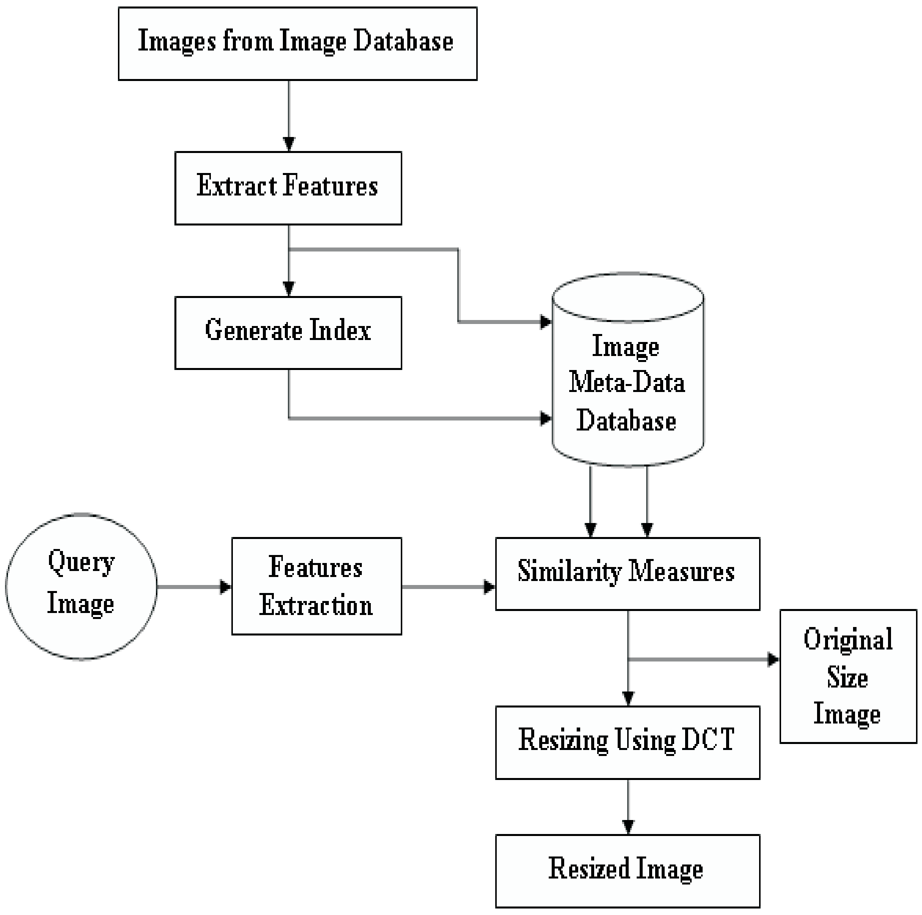

Fig1: Architecture of CBIR &R System

Clustering is a fundamental approach in pattern recognition. The color clustering algorithm that we developed is described as follows:
(1)Transform the image to size 64*64
(2)Obtain the RGB components of an image
(3)Find all color clusters
(i) Compute the color distance of each pixel from the existing color clusters. If no color clusters exist, then set the first pixel as a new cluster. The color distance is given by:
(ii) If the minimum color distance is less than the pre-set threshold, then a match is found. Otherwise, a new color cluster is generated, and set the unmatched pixel as the new cluster.
(iii) For each match, the R, G, B values and the population of the cluster are updated. The new representative color of the cluster is the weighted average of the original cluster and the color of the current pixel.
(3) Compute the population of every cluster. The clusters with a population of less than a threshold are discarded.
(4) For each pixel, compute the color distance to different clusters. Assign the pixel to the cluster to which the color distance is minimum. We consider each cluster as an image layer and each pixel is assigned to one image layer. Fig.3 shows the image layers of the flower image

As mentioned above, images contain objects and peripherals. We can use a color look-up table in which there are object colors and the background colors. Each of image layers will be mapped to either an object color or a background color according to the color distance between the colors of the image layer and a color in the look-up table, Cd, which is defined as:

$$Cd\ (\ \min \sqrt{(Rc\ (\ Rit((\ (Gc\ (\ Git((\ (Bc\ (\ Bit(}$$

Where Rc, Gc, Bc are the values of the color layer and Rit, Git and Bit are the values of ith color in color table.

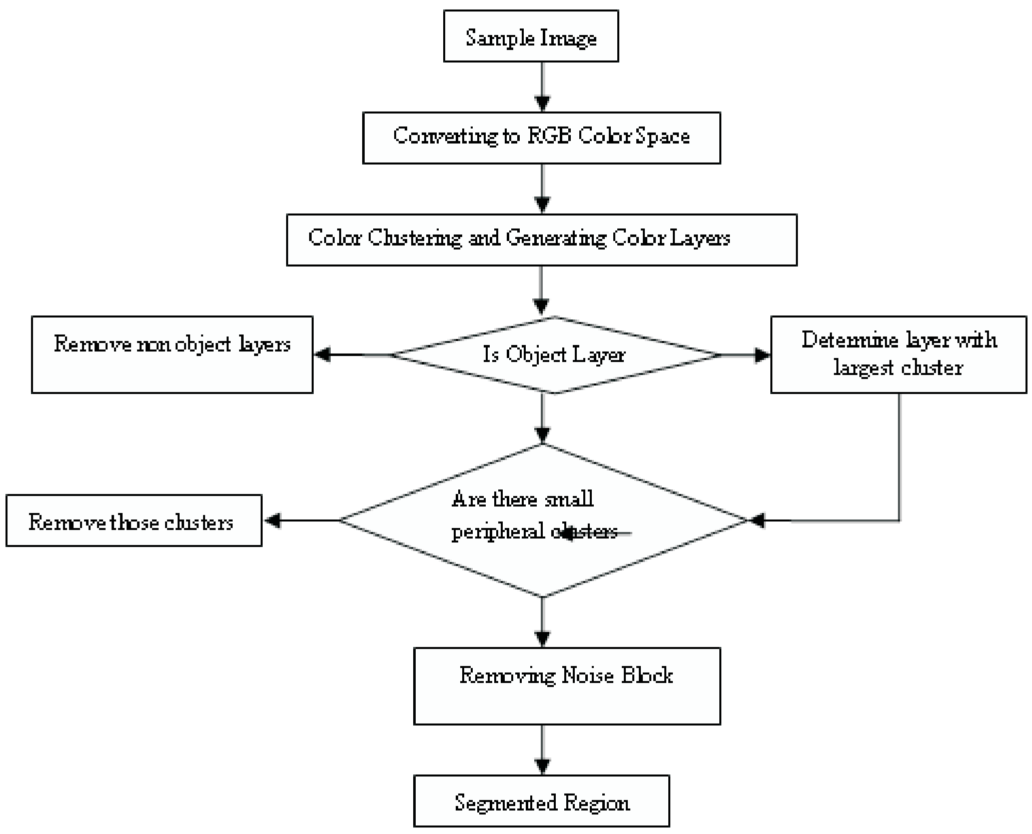

Fig. 2: Flowchart for color cluster analysis

If the layer's color belongs to a background color, we discard the whole layer. Due to diversities of flowers, different illumination conditions, and noise introduced in acquiring the image, we have to consider the following three situations:

1) There is no flower region remained. We will bring back the largest cluster and label it as a main object region. Normally, object region should dominate the image and hence it is quite safe to assume that the largest cluster is an object region.

2) Some background regions are kept as object regions. In general, there are no object regions spread on the narrow peripheral zone (Fig.4). The clusters locating in the narrow peripheral area will be considered as background regions and removed.

3) There are small noise blocks in the object region. Those small blocks in a object layer with size of small than a pre-set threshold (1/10 of size of the largest flower region in the layer) will be removed.

To extract the shape features, the contour of a object region is extracted based on the segmentation. Fig.5 shows the flowchart of our flower image segmentation approach based on clustering and domain knowledge. There may be several flower regions in a flower image. We keep only the longest contour in flower shape analysis.

B. Shape Features

Shape is one of the most important features characterizing an object. Many investigations in shape representation such as chain codes, centroid-contour distance (CCD) curve, and medial axis transform (MAT), Fourier descriptors (FDs), Wavelet descriptions, moment invariants, and deformable templates, had been carried out. All of these features perform well and have advantages for some applications. An important criterion for a good shape representation is that the representation has to be invariant to rotation, scaling, and translation. In this paper, we use two shape features, CCD and angle code histogram (ACH).

C. Centroid-Contour Distance (CCD)

Centroid-contour distance (CCD) can reflect the global character of a shape, but the CCD curve is neither scaling nor rotation invariant. Fig.1 illustrates the definition of the centroid-contour distance curve. Actually, the number of contour points is dependent on the object size. Consequently, the number of CCD curve sample points and the amplitude of CCD samples will change if the scale of the object changes. Based on the maximal and minimal CCD curve values, we can normalize the CCD values to range [0,1] to make it scaling invariant. As to the number of the edge points, we can down-sample the CCD curve with more sample points to make the number of sample points of two CCD curves to be compared equal. The key for a similarity measure with CCD curves to be rotation invariant is to locate fixed starting point(s) of CCD curves. In order to solve this problem, we set the farthest point from the centroid as the start point for each data sample in the database. In retrieving image with a query image, we select several farthest points from the centroid possible start points. The difference between two CCD curves is computed when a possible start point of an enquiry image is aligned with the start point of the database image. The smallest difference between two CCD curves among all possible start points is used to measure the dissimilarity of two contours. We define the distance function to measure the dissimilarity between two CCD curves as:

$$D_c = \sum_{i=1}^{n} | f_1(i) - f_2(i) | / n$$

Where f1(i) and f2(i) are the CCD curves of two object contours at the ith point and n is the total number of the contour points.

D. Angle Code Histogram (ACH)

It was observed that the CCD curve cannot characterize local properties of a contour effectively. However, local properties are very important for the identification of flower shapes. Peng and Chen (1997) proposed an angle code method for shape characterization. In their approach, each closed contour is represented by a sequence of line segments with two successive line segments forming an angle. The angles at contour points on each closed contour were computed and the resulting sequence of successive angles was used to characterize the contour. Angle code has been applied to image retrieval of trademarks and logs. The retrieval process was performed by matching the angle code string. However, flower images are quite different from artificially generated graphics that have ideal lines or arcs. Following the idea of the angle code, we computed the angle for each contour point based on two approximate lines coming to and leaving the point. If the distributions of the angle codes of two closed contours are close, they will have similar local features. We propose to use an angle code histogram (ACH) to characterize the local properties of a image.

If the distributions of the angle codes of two contours are similar, they will have similar local properties. The difference between two angle code histograms is defined as:

$$d = \sum_{j=1}^{K} \left| h_j^{(1)} - h_j^{(2)} \right|$$

Where m is the number of bins in which the angle code histogram is partitioned.

E. Multidimensional Indexing

Multidimensional indexing is an important component of content-based image retrieval. Development of indexing techniques has been an active area. In database management, computational geometry and pattern recognition. However, the notion of indexing has subtle differences in different communities. The notion of indexing in multimedia data mining and content-based image retrieval is different from its notion in the traditional database management systems. In traditional database management systems (particularly for relational databases), the indexing refers t o the access structure of the database files in terms organization of the records. Indexes are specified based on one or more attributes of the records in order to process queries based on those attributes. These record and file structures are well organized and supported by an access structure such as hashing, B-tree, etc. In the information retrieval community, the indexing mechanism is concerned with the process to assign terms (or phrases or keywords or descriptors) to a document so that the document can be retrieved based on these terms. The indexing in content-based image retrieval or mining multimedia data is similar to the notion adopted in the information retrieval. The primary concern of indexing is to assign a suitable description to the data in order to detect the information content of the data. As we explained in the previous sections, the descriptors of the multimedia data are extracted based on certain features or feature vectors of the data. These content descriptors are then organized into a suitable access structure for retrieval.

F. Image Retrieval

The key issues in indexing for content-based image retrieval are:
(1) Reduction of high dimensionality of the feature vectors
(2) Finding an efficient data structure for indexing
(3) Finding suitable similarity measures.

In CBIR, the dimensionality of feature vectors is normally very high. Today the dimensionality is typically of the order of lo2. With the exploration of multimedia content, this order may grow in future. Before indexing, it is very important to reduce the dimensionality of the feature vectors. The most popular approach to reduce high dimensionality is application of the principal component analysis, based on singular decomposition of the feature matrices. The theory behind singular value decomposition of a matrix and generation of principal components for reduction of high dimensionality has been discussed later.. The technique has also been elaborate with regard to text mining. This can be applied to both text and image data types in order t o reduce the high dimensionality of the feature vectors and hence simplify the access structure for indexing the multimedia data. After dimensionality reduction, it is very essential to select an appropriate multidimensional indexing data structure and algorithm to index the feature vectors. There are a number of approaches proposed in the literature. The most popular among them are multidimensional binary search trees, Rtree, variants of R-tree such as R*-Tree, SR-tree, SS-tree, Kd-tree, etc. All these indexing methods provide reasonable performance for dimensions up to around 20, and the performance deteriorates after that. Moreover, most of these tree-based indexing techniques have been designed for traditional database queries such as point queries and range queries, but not for similarity queries for multimedia data retrieval. There have been some limited efforts in this direction. Multimedia database indexing particularly suitable for data mining applications remains a challenge. So exploration of new efficient indexing schemes and their data structures will continue to be a challenge for the future. After indexing of images in the image database, it is important to use a proper similarity measure for their retrieval from the database. Similarity measures based on statistical analysis have been dominant in CBIR. Distance measures such as Euclidean distance, Mahalanobis distance, Manhattan distance, and similar techniques have been used for similarity measures. Distance of histograms and histogram intersection methods have also been used for this purpose, particularly with color features. Another aspect of indexing and searching is to have minimum disk latency while retrieving similar objects. Chang et al. proposed a clustering technique to cluster similar data on disk to achieve this goal, and they applied a hashing technique to index the clusters. In spite of lots of development in this area, finding new and improved similarity measures still remains a topic of interest in computer science, statistics, and applied mathematics.

G. Image Resizing

Scalability of an image representation is required in various applications, such as transmission, storage, retrieval, and display of digital images. For example, in different channels with varying bandwidths, the same image may be transmitted at different spatial (or spectral) resolutions. In internet applications also, for browsing a remote image (or video) database, initially down sampled images may be sent and, depending on the interest and request from the client, images of larger size are sent later. One could directly resize the image in the spatial domain using various interpolation techniques.

But for efficient storage, images are usually represented in the transform domain as compressed data. It is thus of interest to develop resizing algorithms directly in the compressed stream. As discrete cosine transform (DCT)-based JPEG standard is widely used for image compression, a number of approaches have been advanced to resize the images in the DCT space. Very recently, Dugad and Ahuja have proposed an elegant scheme for changing the image sizes in the DCT space. They have suggested a simple fast computation technique for halving and doubling of images using their low-frequency components. The principle behind the algorithms developed by Dugad and Ahuja is similar to the sub band DCT computation. In this work, we propose a modification to their algorithm. In our approach, during doubling of the images, it is not necessary to go back to the spatial domain, if the objective is to get the final result in the spatial domain. It may be noted, however, that Dugad and Ahuja also suggested similar operation. In our work, we have further used a 16*16 DCT transform for obtaining the coefficients in the transformed space for the up sampled image. We have also studied the performances of their scheme along with ours at varying compression rates for typical images. In addition, we have adopted both approaches for the resizing of color images. We observed that our proposed modification performs better than the Dugad-Ahuja method in most cases. It should be noted that Dugad and Ahuja also presented an efficient implementation of their algorithm. In this case, they have used direct matrix multiplication and addition for converting a block (or a set of blocks) of DCT coefficients to a set of blocks (or a block) of DCT coefficients in the resulting image. A similar computation scheme has also been developed for our approaches.

For halving an image in its compressed form (the DCT based JPEG standard), in the first step, the image reduced in size in the spatial domain, is obtained. This is carried out by considering the 4*4 lower frequency-terms and applying a 4-point inverse DCT (IDCT) on them. Hence, from 8*8 blocks, one gets 4*4 blocks in the spatial domain. In the next stage, this image (in the spatial domain) is once again compressed by 8*8 block DCT encoding (JPEG standard). The algorithm is described below.

For doubling the images, first the DCT encoded image is transformed to its spatial domain. Then for each 4*4 block, the DCT coefficients are computed applying a 4-point DCT. These 4*4 DCT coefficients are directly used as the low-frequency components of 8*8 blocks, which are subsequently converted to an 8*8 block in spatial domain by applying an 8-point IDCT.

III EXPERIMENTAL RESULTS

This approach has been evaluated on a flower image as flower images are most colorful & shapeup.

We used (1) the color feature (2) shape features to analyze flower images, out of which color cluster analysis for the separating the different colors in the image give the successful results. The original image and the different image layers are as shown in figure 3. X-Y coordinates of the of the all the pixels from same color layer are obtained and placed in their respective positions, in this way the number of images of different color layers are obtained as shown in figure .

CONCLUSION

In this paper, we first present an effective method to segment object regions from images based on color clustering and domain knowledge. We then discuss the flower image retrieval using three feature sets: the color clustering of image, the Centroid-Contour Distance (CCD) and the Angle Code Histogram (ACH) of the contour. Experimental results on some flower images showed that our approach performs well in terms of color cluster analysis of different objects. Also, this project provides an effective method for the resizing of retrieved image to half of double of its original size.

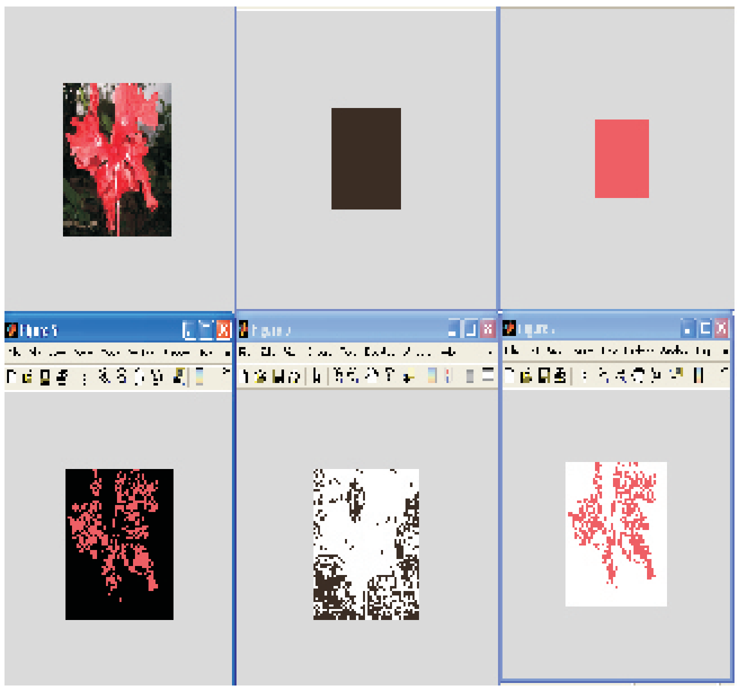

Fig 3: Original image and Different image layers

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