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Content Based Image Retrieval

Nikita R. Patel[1], Dipti Makadia[2]

[1]Assistant Professor, [2]Software Developer

BVM Engineering College-V.V.Nagar[1], Maruti Tech.labs-Ahmedabad[2]

Abstract – *This Article present a Content Based Image Retrieval (CBIR) is any technology this principle helps to organize digital image archives by their visual content. Conventional databases allow for textual searches on Meta data only. Content Based Image Retrieval (CBIR) is a technique which uses visual contents, normally called as features, to search images from large scale image databases according to users' requests in the form of a query image.*

Keywords: Component – CBIR; QBE; QBME; FCM

I. INTRODUCTION

An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval utilize metadata such as captioning, keywords, or descriptions to the images. So that retrieval can be performed over the annotation words.

Problem Domain for Text Based Image Retrieval

There are several problems of image annotation like large volumes of databases Valid only for one language with image retrieval this limitation should not exist. Text based retrieval is oriented with several language, so there is the need of language independent retrieval. Problem of human perception subjectivity .Too much responsibility on the end-user. There is also the problem of deeper (abstract) needs .Queries that cannot be described at all, but tap into the visual features of images. The previous work by the researchers of image retrieval, images was manually annotated. It was costly; this was affordable for only large organizations.

Solution: Content Based Image Retrieval

Content Based Image Retrieval (CBIR) is any technology that in principle helps to organize digital image archives by their visual content. By this definition, anything ranging from an image similarity function to a robust image annotation engine falls under the preview of CBIR. The most common form of CBIR is an image search based on visual .The increasing amount of digitally produced images requires new methods to archive and access this data.

Conventional databases allow for textual searches on Meta data only. Content Based Image Retrieval (CBIR) is a technique which uses visual contents, normally called as features, to search images from large scale image databases according to users' requests in the form of a query image.

CBIR can greatly enhance the accuracy of the information being returned and is an important alternative and complement to traditional text-based image searching. For describing image content, color, texture and shape features have been used. Color is one of the most extensively used low-level visual features and is invariant to image size and orientation. There are color histogram, color moments as conventional color features used in CBIR. Without any other information, many objects in an image can be distinguished solely by their textures. Texture may describe the structural arrangement of a region and the relationship of the surrounding regions and may also consist of some basic primitives. Shape feature has been extensively used for retrieval systems.

II. RELATED RESEARCH

Feature Extraction for CBIR

The CBIR system relies on color, texture and shape which are low level image features .The low level features are extracted from the database images and stored in a feature database. Similarly, the low level features are extracted from the query image and the query image features are compared with the database image features using the distance measure. Images having the least distance with the query image are displayed as the result.

Low Level image Features used in CBIR

In CBIR systems, a feature is a characteristic that can capture a certain visual property of an image either globally for the entire image or locally for regions or objects. The low level features commonly used in CBIR are color, texture, shape and edge. The following subsections address the color, texture, shape and edge features used in CBIR.

Color Features

Color feature is the most intuitive and obvious feature of the image, and generally adopt histograms to describe it. Color histogram's method has the advantages of speediness, low demand of memory space and not sensitive with the images 'changes of the size and rotation, it wins extensive attention consequently**.** Color features are extracted using color moments, color histogram, and dominant color.

Color Moments

The color distribution of the image is characterized by its moments. The first, second and third central moment of each of the color channels is stored as a color feature. If the value of the i^{th} color channel at the j^{th} pixel is p_{ij}, then the first moment mean ( ) is given by equation (1). The second moment standard deviation () is given by equation (2). The third moment skewness () is given by equation (3).

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} P_{ij} \qquad (1)$$

$$\sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N}(P_{ij}-\mu_i)^2\right)^{\frac{1}{2}} \qquad (2)$$

$$\gamma_i = \left(\frac{1}{N}\sum_{j=1}^{N}(P_{ij}-\mu_i)^3\right)^{\frac{1}{3}} \qquad (3)$$

N in equation (1) to (3) is the total number of images.

Color Histogram

The histogram of an image is a graph which contains the occurrence of each intensity value found in that image, obtained by counting all image pixels having that intensity value. For an 8-bit grayscale image there are 256 different possible intensities. So, the histogram will graphically display 256 grayscale values showing the distribution of pixels amongst those numbers. Histograms can also be taken of color images. A color histogram is the representation of the distribution of colors in an image. It is a standard statistical description of the color distribution in terms of the occurrence frequencies of the different regions in a color. To create a color histogram, the color space has to be partitioned into regions. The 24 bit RGB color space has 224 different color regions. A histogram containing 224 bins is too large to be dealt. Hence the color space is quantized into a number of bins, where each bin represents a range of color values. The number of pixels in the image that falls in each of these ranges is counted to get the color histogram. The number of bins is decided based on the loss of precision tolerated and the memory requirement. Color histograms can be built in various color spaces.

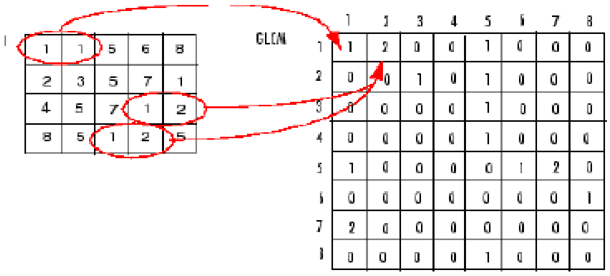
Dominant Color

In region based image retrieval, the regions are segmented and the features are extracted for the regions. Due to the inaccuracy of the segmentation, the average color of a segmented region may be different from that of the original region. To obtain the dominant color of the image, first the histogram is obtained and then the bin with the maximum size is taken as the dominant color of the region. When the segmented region does not have a homogeneous color, then, the average color will not be a good choice for the color feature.

Texture Features

When it refers to the description of the image's texture, we usually adopt texture's statistic feature and structure feature as well as the features that based on spatial domain are changed into frequency domain. Texture features are extracted using Gray Level Co-occurrence matrix (GLCM), Gabor Transform and Tamura Features. These methods of extracting texture features are explained in the following section.

Gray Level Co-occurrence matrix (GLCM) The GLCM is created from a gray-scale image. The GLCM finds how often a pixel with a gray-level value i occurs either horizontally, vertically, or diagonally to adjacent pixels with the value j. It is given by the relative frequency of the occurrences of two gray-level pixels i & j, separated by d pixels in the θ orientation, where d is the displacement and θ is the direction. The _d' can take values 1, 2, 3, etc., and θ can take values 0° (horizontal), 90° (vertical), 45° and 135° (diagonal) (Rahman et al., 2007). The construction of the GLCM is shown in Figure 1. Several statistical texture properties like contrast, correlation, energy, homogeneity and entropy can be derived from the GLCM and the formulae are given in equations (5) through (9).



$$Contrast = \sum_i \sum_j |i-j|^2\, p(i,j) \qquad (5)$$

$$Correlation = \sum_i \sum_j \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i\, \sigma_j} \qquad (6)$$

$$Energy = \sum_i \sum_j p(i,j)^2 \qquad (7)$$

$$Homogeneity = \sum_i \sum_j \frac{p(i,j)}{1+|i-j|} \qquad (8)$$

$$Entropy = \sum_i \sum_j p(i,j) \log\big(p(i,j)\big) \qquad (9)$$

Tamura Features

Coarseness, contrast, directionality, line-likeness, regularity and roughness are the six Tamura features. Coarseness, contrast and directionality correlate strongly with the human perception, and hence they are very important.

Shape Features

Shape may be defined as the characteristic surface configuration of an object; an outline or contour. It permits an object to be distinguished from its surroundings by its outline. Shape representations can be generally divided into two categories:

Boundary-based, and
Region-based.

Boundary-based shape representation only uses the outer boundary of the shape. This is done by describing the considered region using its external characteristics; i.e., the pixels along the object boundary. Region-based shape representation uses the entire shape region by describing the considered region using its internal characteristics; i.e., the pixels contained in that region.

III. PROPOSED WORK

<u>CBIR Techniques</u>

1) Query techniques

a) Query by example image (QBE)

This is the classical content-based image search paradigm. The user provides a sample image with the intention of having the system retrieve similar images. An example of a system that allows searching by this paradigm is QBIC. There are shortcomings to this approach. Most significantly, query by example image requires that a user acquire a representative image before querying. This image may be from another collection, obtained through means beyond the particular CBIR system.

b) Query by image region

Queries can be based on a user or system-defined subset of an entire region. In order to accomplish this the user must be allowed to manually-define a region of the image, or an unsupervised method of segmentation must be incorporated into the system.

c) Query by multiple example images (QBME)

The user can provide several example images to the system. Commonalities between all the query images can be used the basis of the query.

d) Query by visual sketch

Several implementations provide drawing tools for the user to create an arbitrary image, the challenge of this approach is that is relies on the artistic abilities of the user, resulting in one of the most demanding query interfaces.

e) Query by keyword

If images have previously been annotated or if textual contest is available it is possible to search them using text. Google Image Search is a successful example of this method .Google Image Search automatically annotates images by using the surrounding text of the web page on which the image appears. Query by keyword systems can also rely on manual annotation of individual images by humans. This is an effective query method that may operate entirely in the absence of image content, although it is not always feasible to annotate images in a suitable fashion.

2) Content comparison using image distance measures

The most common method for comparing two images in content-based image retrieval (typically an example image and an image from the database) is using an image distance measure. An image distance measure compares the similarity of two images in various dimensions such as color, texture, shape, and others. For example a distance of 0 signifies an exact match with the query, with respect to the dimensions that were considered. As one may intuitively gather, a value greater than 0 indicates various degrees of similarities between the images. Search results then can be sorted based on their distance to the queried image.

A) Relevance feedback using random walks based Technique

Overview

The concept of relevance feedback, consists of using user feedback to judge the relevance of search results an d therefore improve their quality through iterative steps .Moreover, by gathering feedbacks from the user a CBIR system can dramatically boost its performance by reducing the gap between the high-level semantics in the user's mind and low-level image descriptors.

Different feedback models have been proposed. positive feedback, which allows the user to select only relevant (positive) images; positive–negative feedback, where the user can specify both relevant and non- relevant (negative) images; positive–neutral–negative feedback, where also a neutral class is added among the user's choices; and feedback with (non)relevance degree, where the user implicitly ranks the images by specifying a degree of (non)relevance. The new information inferred from the user can then be used within a short-term-learning or long-term-learning process. The former uses the user feedback only within the user's query context, while the latter updates the image similarities in order to benefit from the feedback in future queries.

The problem of CBIR with relevance feedback can be seen as the problem of ranking a setoff images in a way as to have images visually consistent with a query image appearing earlier in the ordering. The first K images in the ranking are presented to the user, who has the opportunity of marking them as relevant or non-relevant if not satisfied with the result. The user' s feedback can then be used in order to bridge the semantic-gap between what he perceives as similar and what he provided low-level similarities classify as similar.

We formalize the user, who makes the query and is involved in the feedback rounds ,as a function which labels images, and thus vertices of G, as relevant(1)or non-relevant(0).

Low Level Feature Extraction

Color and Shape feature extraction are used. Color moments and Color histogram are used to extract color feature. Shape feature is extracted using Gray level co-occurrence matrix (GLCM).

Conclusion

A novel approach to CBIR with relevance feedback, which is based on the random walker algorithm introduced in the context of interactive image segmentation. Relevant and non-relevant images labelled by the user at every feedback round are used as ''seed'' nodes for the random walker problem. Each unlabelled image is finally ranked according to the probability that a random walker starting from that image will reach a relevant seed before encountering a non-relevant one.

B) Fuzzy C-means Algorithm (FCM) based approach for Shape Extraction overview

In attempt to further improve the CBIR technique presented an improved algorithm by extracting feature vector comprises of shape and color from image. In this approach the image feature vector is then used to search the image in dynamic environment like Google or Yahoo search engine. Fuzzy C-Mean clustering algorithm is used for segmentation. After successful segmentation boundary of the extracted object is converted into signature whose Fast Fourier Transform is calculated. FFT provide the array vector corresponding to the number of regions obtained after segmentation and is stored in database as first feature vector.

Low Level Feature Extraction

Shape and color is used to represent low level visual content of the image.

Segmentation based on FCM

Step 1: For query image, find out the clusters and its corresponding centre using FCM clustering approach.

Step 2: Apply connected component procedure in order to get connected regions or mask using segment mask and number of segments as input. For connected component procedure we use 4-connectivity.

Signature Development

For signature development use the actual image, region mask and number of regions obtained using segmentation as inputs. Generate the signature of the query image by combining the signature of the region mask.

Conclusion

The fuzzy C-means algorithm (FCM) generalizes the hard c-means algorithm to allow a point to partially belong to multiple clusters. Therefore, it produces a soft partition for a given dataset. In fact it produces a constrained soft partition. A feature extraction approach, called “Fast Fourier Transform”, to extract the invariant array vector from signature obtained after segmentation of the image. The derived array vector is later used to form a first feature vector along with the HSI component of color image, which will be used as second feature vector. Results this algorithm is able to perform much better than traditional methods of Content based Image Retrieval.

C) Ranklet Transform Based Approach for Texture Extraction

Overview

Early studies on CBIR used a single visual content such as color, texture, or shape to describe the image. The drawback of this method is that using one feature is not enough to describe the image since the image contains various visual characteristics. Here, both color and texture features extraction from the image is used. Color and texture feature extract are simpler compared to other features.

Low Level Feature Extraction

It uses both color and texture feature. To extract the color feature from the image, the color moment will be calculated where the image will be in the HSV color space. To extract the texture feature, the image will be in Gray-scale and Ranklet Transform is performed on it.

Ranklet Transformation

Before we extract the texture feature from the image, we perform a pre-processing step using Ranklet Transform. The result of applying Ranklet Transform on the image is 3 Ranklet images in different orientation (vertical, horizontal, and diagonal). Ranklet Transform belongs to a family of nonparametric, orientation-selective, and multi resolution features that has the wavelet style. It has been used for pattern recognition and in particular to face detection. Later on, it has been used for testing and estimating 3D structure and motion of Objects .Ranklet Transform has been used in medical fields. It has been applied to the problems of tumoral masses detection in digital mammograms. Some tests show that Ranklet Transform performs better than some methods such as pixel-based and wavelet-based image representations. Ranklet Transform has three main properties. First, it is nonparametric that it is based on nonparametric statistics that deal with a relative order of pixels instead of their intensity values. Second, it is orientation selective that it is modelled on Haar wavelets. This means that for an image, vertical, horizontal, and diagonal Ranklet coefficients are computed. Finally, it is multi resolution that the Ranklet Transform can be calculated at different resolutions using Haar wavelet supports. The powerful of using Ranklet Transform as a pre-processing step is to make the image invariant to rotation and any image enhancement operations To calculate the texture moments for each ranklet image ,we have to calculate the ranklet histogram (*rh*) and the ranklet co-occurrence matrix (*rcmd,θ*), where

$$rh(i) = \frac{n(i)}{\sum_{j=1}^{21} n(j)} \qquad i, j = 1, 2, \dots, 21$$

$$rcmd, \theta = \frac{n_{d,\theta}(i,j)}{\sum_{l=1}^{21} \sum_{k=1}^{21} n_{d,\theta}(l,k)}$$

Where *n(i)* is the number of ranklet coefficients in the ranklet image taking value *rv(i)* = (- 1, -0.9, …, -0.1, 0, +0.1,…, +0.9, +1).

Now we can calculate Texture feature by using formulas for Code Entropy and Variance.

Conclusion

In CBIR, the most commonly used performance measures are Precision and Recall. We denote to the precision by P. The equation of precision is:

$$\mathrm{P} = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ images\ retrieved}$$

We denote to the recall by R. The equation of recall is:

$$R = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ relevant\ images\ in\ the\ database}$$

Perform some experiments to check the retrieval effectiveness of the proposed method. Some images were selected randomly from each category to test the system. The testing process is divided into 3 phases. In the first phase, the proposed method will use the randomly selected images to retrieve similar images from the database using the color feature only. The precision is calculated for each experiment and for each category. In the second phase, the proposed method will retrieve similar images from the database using the texture feature only. Also, the precision is calculated for each experiment. In the third phase, the proposed method will retrieve images similar to the input image according to the color feature and the texture feature. It is clear that it works very well when we use both color and texture feature to retrieve images similar to the input image. Also, using the combination of color and texture features to represent the image and retrieve images similar to it has more accuracy compared with only color feature or only texture feature.

E) Edge Histogram Descriptor(EHD) based Approach for Edge density Feature Extraction

Overview

A combination of three feature extraction methods namely color, texture, and edge Histogram descriptor. There is a provision to add new features in future for better retrieval efficiency. Any combination of these methods, which is more appropriate for the application, can be used for retrieval. This is provided through User Interface (UI) in the form of relevance feedback. The image properties analysed in this work are by using computer vision and image processing algorithms.

Low Level Feature Extraction

It uses Color, Texture and Edge Density feature Extraction from images. For color the histogram of images are computed, for texture co-occurrence matrix based entropy, energy, etc., are calculated and for edge density it uses Edge Histogram Descriptor (EHD).

Edge Histogram Descriptor (EDH)

The Edge Histogram Descriptor represents the local edge distribution in the image which is obtained by subdividing the whole image into 4 × 4 sub images. For each of these sub images we compute the histogram. This means a total of 16 × 5 = 80 bins are required. The histograms are categorized into four directional edges called vertical, horizontal, 45 degree, 135 degree, and one non-directional edge. To detect the edge strength, filter coefficients shown in Figure were applied. Edge blocks that are greater than a given threshold is selected.

1	-1	1	1	$\sqrt{2}$	0	2	-2
1	-1	-1	-1	0	$-\sqrt{2}$	-2	2

Filter Coefficients

For each sub image the edge density can be calculated using equation (6). Let (x1, y1) and (x2, y2) are the top left corner and the bottom right corner of the sub image. Then the edge
Density f is given by,

$$f = \frac{1}{a_r} \sum_{x=x1}^{x2} \sum_{y=y1}^{y2} e(x, y)$$

Where ar is the region area. All these features are put in the feature vector table.

Conclusion

This paper proposed a universal model for the Content Based Image Retrieval System by combining the color, texture, and edge density features or individually. Users were given options to select the appropriate feature extraction method for best results. The advantages of global and local features together have been utilized for better retrieval efficiency. The results are quite good for most of the query images and it is possible to further improve by fine tuning the threshold and adding relevance feedback.

V. CONCLUSION & FUTURE WORK

Most traditional and common methods of image retrieval utilize metadata such as captioning, keywords, or descriptions to the images. So that retrieval can be performed over the annotation words.In this paper we conclude that CBIR involves the four parts data collection, build up feature database, search in the database, arrange the order and deal with the results of the retrieval. The real world requirements are Face Recognition, Biodiversity, Information System Art Collections, Scientific Databases, Medical science and so far.

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