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A Survey on Feature Extraction Techniques in Content-based Image Retrieval

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ABSTRACT: The rapidly expanding image collections on the Internet and the emergence of multimedia technology have attracted significant research efforts in generating tools for effective retrieval of visual data. Difficulties faced by text-based image retrieval brought the researchers to invent new solutions to represent and index visual information. This new trend of image retrieval was based on properties that are inherent in the images themselves and was called Content-Based Image Retrieval. Content-Based Image Retrieval (CBIR) uses the visual contents of an image such as color, shape, texture, and spatial layout to represent and index the image. Active research in CBIR is geared towards the development of methodologies for analyzing, interpreting, cataloging and indexing image databases. In addition to their development, efforts are also being made to evaluate the performance of image retrieval systems. The quality of response is heavily dependent on the choice of the method used to generate feature vectors and similarity measure for comparison of features. The research in CBIR field is motivated by the large amount of potential applications that the new technologies offer.

KEYWORDS: Content Based Image Retrieval, Color, Shape, Lab space, HSV.

I. INTRODUCTION

The advancement of modern technology, computational power of processors and reduction in the price of memory causes need to switch from the historical approach to the new approach. Maintenance of huge databases is very crucial and especially when large collection of digital images need to be maintained. In many areas where digitized images are required like Academia, Multimedia, Journalism, Hospitals, GIS, Crime Prevention, Pattern Recognition, Statistics and many more. Thus over the decade the volume of digital image is increasing very exponentially. Thus several researchers are working on it to maintain the huge amount of databases.

Historical approach of searching the image was simply by browsing or by indexing. Problem with the historical approach leads to another way of accessing the image on the basis of their content or feature. This new trend of image retrieval was based on properties that are inherent in the images themselves and was called Content-Based Image Retrieval.

Content-Based Image Retrieval (CBIR) uses the visual contents of an image such as color, shape, texture, and spatial layout to represent the image and also for index the image. The block diagram (Fig 1) of a CBIR system can be understood as a basic building blocks that communicate with each other to retrieve the database images according to a given query. In normal content-based image retrieval system (Fig 1) the visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature database made by thesefeature vectors of the images. To retrieve images, users provides query images to the retrieval system. The system then changes the query image into its internal representation of corresponding feature vectors. The similarities as well as differences between the feature vectors of the query image and the images in the database are then calculated and retrieval is performed with using some indexing schemes. Now a days, some CBIR systems make use of a module related to the relevance feedback, where the user progressively refines the search results by marking images in the results as "relevant", "not relevant", or "neutral" to the search query, then repeating the search with the new information. Thus, from the query results, the user can evaluate which images are relevant.Also the system can reuse their information in order to refine their results.

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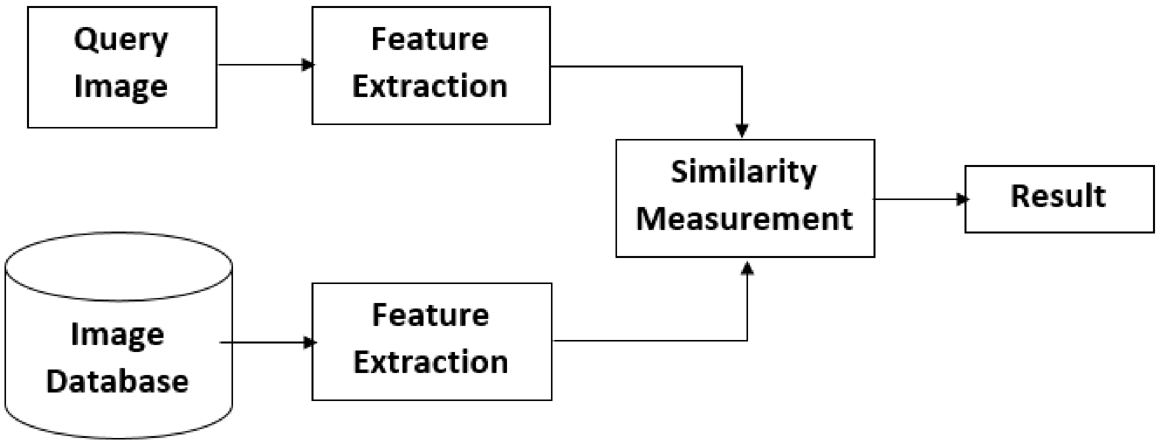

Fig.1.Block diagram of content-based image retrieval system

We noted some Characteristics of CBIR include like Image retrieval by image content, Visually similar images to Query image, No keywords, Low level features like color, shape are used, etc.

The rest of the paper is as follows. Section 2 briefs the considered different schemes based on CBIR for the analysis. Section 3 represents the feature extraction techniques considering different features. Section 4 represents the similarity measurement and the paper concludes with section 5.

II. LITERATURE SURVEY

From the past decade, the search for highly effective and efficient techniques of CBIR is a dynamic focus of research. The comprehensive works of talwar [3], Bansal [9] provide some of the most influential surveys on the CBIR. The extensive work of Singh [2], Chaudhari[4], Daisy [6] and Apurva [10] also outstands to describe the functionality of CBIR systems. Pujari [1], Sarvanan [7] done a great work with color feature. Finally, the recent study of Xie [5], Gui [8] and Demir [11] gives an actual overview of the enhanced of CBIR and tackle its major future challenges by implementing the relevance feedback using supervised learning algorithms.

III. FEATURE EXTRACTION

The basis of any content-based image retrieval technique is a visual feature extraction. In a bigger sense, features may include both visual features (color, shape, etc.) and text-based features (key-words, annotations). The visual feature scope can be further classified as high-level features and low-level features. One of the keys of a CBIR system is the selection of the features to represent an image. There does not exist a single best representation for any given visual feature because of the complex composition and perception subjectivityof visual data. Multiple approaches have been introduced for each of these visual features and each of them characterizes the feature from a different perspective [3].

3.1 Color:

Color is a perception that depends on the response of the human visual system to light and the interaction of light with objects [1] [7]. It is the product of the surface spectral reflectance, illuminant and sensor sensitivity (i.e. of digital sensors or of cones in the human eye). Color is widely used visual features in content-based image retrieval among all the features. It is relatively robust to background complication.It is independent of image orientation and size. The key issues in color feature extraction include the color space, color quantization, and the choice of similarity function [3]. We have to first determine the color space to use, if we want to describe an image by its color features. There exist

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different space models such as RGB, HSV, CIE L*a*b*, etc. The best representation depends on the special needs of the application.

3.1.1 Color Space:

There are different color spaces currently used for the representation of images in the real world. Choosing an appropriate color space for the implementation of a content based image retrieval system is as much important as the production of the accurate results. The accurate representation of color in the way that the human visual system perceives it. Here some of the most commonly used are:

3.1.1.1 RGB

RGB[1] stands for Red-Green-Blue. RGB is the most popular color space. This space consists of the additive primary color of light Red, Green and Blue. To produce more or less any color in the visible spectrum, varying levels of the three colors are added. RGB color space is device dependant and perceptually non-uniform. This means that a color relative close together in the RGB space hard to be perceived as being close by the human eye. RGB space is normally used in television, scanners, Cathode Ray Tube (CRT) monitors and digital cameras. For a monitor the phosphor luminescence consists of additive primaries and we can simply parameterize all colors via the coefficients (α, β, γ), such that $C = \alpha R+\beta G+\gamma B$. The coefficients range from zero (no luminescence) to one (full phosphor output). In this parameterization the color coordinates fill a cubical volume with vertices black, the three primaries (red, green, blue), the three secondary mixes (cyan, magenta, yellow), and white.

3.1.1.2 HSV

Colors in the HSV[1] color space are defined in terms of three constituent components; Hue, Saturation and Value. Hue represents color. In this model, hue is an anglefrom 0 degrees to 360 degrees. Saturation indicates the range of grey in the color space. Itranges from 0 to 100%. Sometimes the value iscalculated from 0 to 1. When the value is '0,' the color isgrey and when the value is '1,' the color is a primarycolor. A faded color is due to a lower saturation level, which means the color contains more grey.Value is the brightness of the color and varies with colorsaturation. It ranges from 0 to 100%. When the value is '0'the color space will be totally black. With the increase inthe value, the color space brightness up and shows variouscolors as in fig.2.

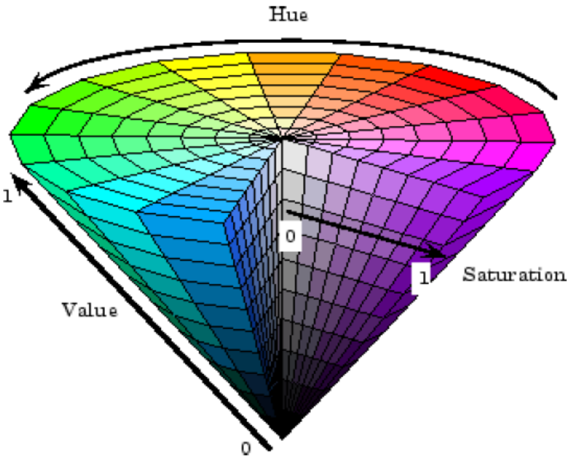

Fig.2.HSV color space [1]

*3.1.1.3 L*a*b*

CIE L*a*b* [1] spaces are suitable models for image retrieval since they accomplish the requirement of spatial uniformity. These are perceptually uniform color spaces and are totally device independent representations of color. The three components of the model represent the lightness (L*) and two chromatic components; a* and b* showing the distance between magenta and green, and yellow and blue respectively as shown in fig.3. CIE L*u*v* was an attempt

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to linearize the perceptibility of the color differences.Accordingly the Labcolor space approach gives better performance than RGBand HSV [1].

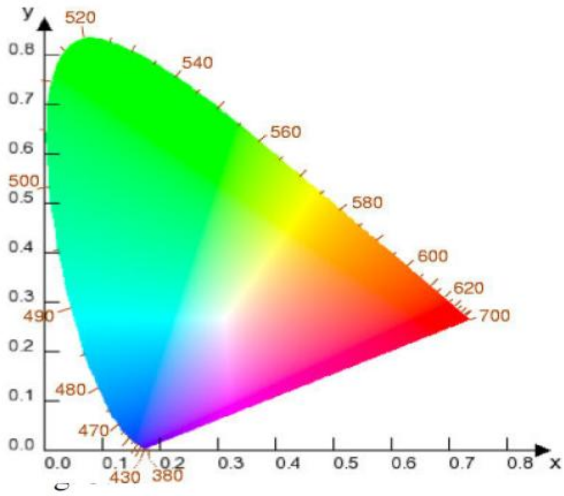

Fig.3.L*a*b color space[1]

3.1.2 Methods of representation
Each feature may have several representations as color histograms [7], color moments [2], color coherence vectors [10] image color feature. Moreover, numerous variations of the color histogram itself have been proposed which differs in the selected color-quantization scheme as we studied. The mathematical operations of the pixel values represented in a certain color space are related to color descriptors. Some of the most popular descriptors are:

3.1.2.1 Color histogram
The main method of representing color information of images in CBIR systems is through color histograms [7]. A color histogram is a type of bar graph, where each bar represents a particular color of the color space being used. Statistically, a color histogram is a way to approximate the joint probability of the values of the three color channels. By splitting the range of the data into equally sized bins we get the most common form of the histogram. Then for each bin, the number the colors of the pixels in an image that fall into each bin are counted and normalized to total points, which gives us the probability of a pixel falling into that bin. It does not take into consideration the spatial information of pixels is one of the main drawbacks of the color histogram. If two images have similar color distributions, still very different images can be considered similar.

3.1.2.2 Color Moments
To avoid the quantization drawbacks, Stricker and Orengo proposed using the color moments approach [2]. Color moments are the statistical moments of the probability distributions of colors and have been successfully used in many retrieval systems, especially when the image contains just the object. The first order (mean), the second (variance) and the third order (skewness) color moments have been proved to be efficient and effective in representing color distributions of images. Color moments also fail to encode any of the spatial information surrounding the color within the image and so suffer from similar problems to the color histogram approach.

3.1.2.3 Color coherence vector
A color coherence vector is a split histogram which partitions pixels according to their spatial coherence. Each pixel within the image is partitioned into two types, i.e., coherent or incoherent according to whether it is part of a larger region of uniform color. Separate histograms can then be produced for both coherent and incoherent pixels thereby including some spatial information in the feature vector. Due to its additional spatial information, it has been shown that CCV provides better retrieval results than the color histogram, especially for those images which have either

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mostly uniform color or mostly texture regions. In addition, for both the color histogram and color coherence vector representation, the HSV color space provides better results than RGB and CIE L*a*b* space.

3.2 Shape:

Shape is usually represented verbally or in figures, and people use terms such as elongated, rounded etc. Computer-based processing of shape requires describing even very complicated shapes precisely and while many practical shape description methods exists, there is no generally accepted methodology of shape description. Shape is an important visual feature and it is one of the primitive features for image content description. It contains all the geometrical information of an object in the image which does not change generally change even when orientation or location of the object are changed. Some simple shape features are the perimeter, area, eccentricity, symmetry, etc.

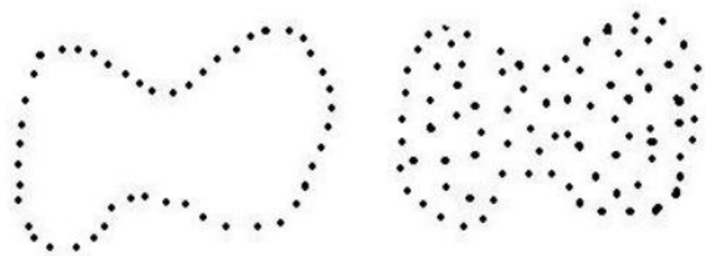

Fig.4.Boundary-based & Region-based shape representations [3]

3.2.1 Methods of representation

Two major steps are involved in shape feature extraction: object segmentation and shape representation. Their shape features can be represented and indexed, once objects are segmented. In general, shape representations can be divided into two categories, boundary-based and region-based (Fig 4). The boundary-based uses only the outer boundary of the shape while the region-based uses the entire shape region. Examples of the first type include chain codes, Fourier descriptors, simple geometric border representations (curvature, bending energy, boundary length, signature), and examples of the second include area, Euler number, eccentricity, elongatedness, and compactness. The most successful representation for thesetwo categories are Fourier descriptors and moment variants.

3.3 Similarity Measurement

The main objective of a CBIR query is to efficiently search and retrieve images from a database that are similar to the query image specified by a user. To finding good similarity measuresbetween images is a challenging task. Similarity measurement is the process of finding the similarity/difference between the database images and the query image using their features [3][8]. The database image list is then sorted according to the ascending order of distance to the query image and images are retrieved from the database according to that order. The choice for a particular measure can affect significantly the retrieval performance depending on their characteristics and the particular needs of the retrieval application. Some of the commonly used measures are:

3.3.1 Minkowski-Form distance

The Minkowski-Form distance [3][10] is the most widely used metric for image retrieval, Given two feature vectors f1 and f2 of N bins, this measure is defined as follows

$$D(f1, f2) = (|f1\ i - f2N1(i)|p)1/p$$

In this measure each dimension of image feature vector is independent of each other and is of equal importance. Depending on the value of the parameter we talk about three types of distances. When p = 1, the Minkowski-Form corresponds to the Manhattan Distance (or city-block) (L1), when p = 2 we talk about the Euclidean Distance (L2), and when p = ∞ it is called is Chebyshev Distance (L∞).

3.3.2 Euclidean Distance

Euclidean distance [3][10] is the most common metric for measuring the distance between two vectors and is discussed and implemented in a number of content based image retrieval approaches. It is applicable when the image feature vector elements are equally important and the feature vectors are independent of one another. The Euclidean distance can simply be described as the ordinary distance between two values. It is given by the square root of the sum of the squares of the differences between vector components. The Euclidean distance between the feature vectors P = (p1, p2, ….., pn) and Q = (q1, q2,….. qn) is expressed by

$$D = (pk-qk)2nk=1$$

Where n is the length of the feature vector and D is the distance between the two vectors. The Euclidean distance provides the most obvious approach to calculating the distance between two feature vectors along with one that is very simple to implement with a low level of complexity. For these reasons it provides a good method for feature vector comparison.Several CBIR commercial systems make use of the Euclidean distance. [3] Used Euclidean distance for color and shape feature; [6] used Euclidean distance for texture and shape feature.

3.3.3 Manhattan distance

If the Euclidean distance is considered as the straight line distance between points then the Manhattan distance [3][10] is the two sides of a square approach. It is this that gives the technique its name since Manhattan is laid out in city blocks forcing you to walk 2 sides of a square in order to get anywhere. The Manhattan distance between feature vectors P = (p1, p2,….., pn) and Q = (q1, q2,….. qn) is expressed by

$$D = |pk- qk|nk=1$$

Where n is the length of the feature vector, D is the distance between the two vectors.

IV. CONCLUSION AND FUTURE WORK

The area of content-based image retrieval is a very huge research area that works for different features like color, shape and much more. CBIR is a hybrid research area that requires knowledge of both computer vision and of database systems.We can make a better system by combining different features to retrieve accurate image as an output. In future relevance feedback also be our aim of research.

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BIOGRAPHY

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