Content-based Image Retrieval: Feature Extraction Techniques and Applications

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ABSTRACT

The emergence of multimedia technology and the rapidly expanding image collections on the Internet have attracted significant research efforts in providing tools for effective retrieval and management of visual data. The need to find a desired image from a large collection is shared by many professional groups, including journalists, design engineers and art historians. Difficulties faced by text-based image retrieval brought the researchers to develop 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" means that the search will analyze the actual contents of the image. Image content descriptors may be visual features such as color, texture, shape or spatial relationships. The research in CBIR field is motivated by the large amount of potential applications that the new technologies offer.

General Terms

Information Retrieval, Database Management, Computer Vision.

Keywords

Content-based image retrieval, feature extraction, similarity measures, Euclidean distance.

1. INTRODUCTION

Information Retrieval is the field of knowledge that deals with the representation, storage, and access to information items. More specifically, when the retrieved information is a collection of images, this field of knowledge is called *Image Retrieval*. The origins on Image Retrieval can be traced back to 1979 when a conference on Database Techniques for Pictorial Applications was held in Florence [1]. Since then, the application potential of image database management techniques has attracted the attention of researchers. Early techniques were not based on visual features but on the textual annotation of images. However, this purely text-based approach posed two significant limitations in the retrieval of images. The first limitation was related to the volume of the database. Manual annotation was such a cumbersome and expensive task that it could not be applied to large image databases. The second limitation which affected the performance of the system was that the description of the images was found to be a highly subjective task that could generate different text labels to the same image. Problems with such methods of image indexing [2] have led to the rise of interest in techniques for retrieving images on the basis of automatically-derived features such as color, texture and shape – a technology now generally referred to as content-based image retrieval.

In the past decade, many CBIR systems have been developed. Many of the examples include the IBM QBIC System, the MIT Photobook System, the Berkeley Chabot and Blobworld Systems, the Virage System, Columbia's VisualSEEK and WebSEEK Systems, the PicHunter System, UCSB's NeTra System, UIUC's MARS System, the PicToSeek System, and Stanford's WBIIS and SIMPLIcity Systems.

2. CONTENT-BASED IMAGE RETRIEVAL

Content-based image retrieval (CBIR) is a technique for retrieving images on the basis of automatically-derived features such as color, texture and shape. The architecture of a CBIR system can be understood as a basic set of modules that interact within each other to retrieve the database images according to a given query. In typical 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 vectors of the images in the database form a feature database. To retrieve images, users provide the retrieval system with query images or sketched figures. The system then changes the query image into its internal representation of feature vectors. The similarities/differences between the feature vectors of the query example and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme. Some CBIR systems make use of an optional 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 and the system can reuse their information in order to improve the results.

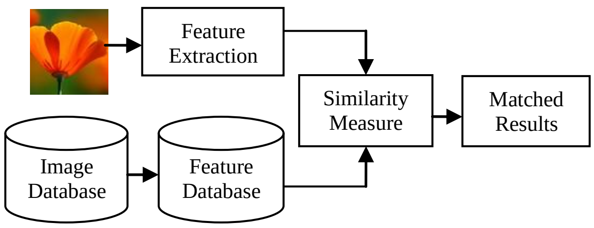

Fig 1. Block diagram of content-based image retrieval system

Nowadays, the search for effective and efficient techniques of CBIR is still a dynamic focus of research. The comprehensive works of Rui [3], Eakins [4] and Smeulders [5] provide some of the most influential surveys on the CBIR until year 2000. The extensive work of Veltkamp [6] also outstands to describe the functionality of more than 50 CBIR systems. Finally, the recent study of Datta [7] (2008) gives an actual overview of the fundamentals of CBIR and discusses its major future challenges.

3. FEATURE EXTRACTION TECHNIQUES

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

3.1 Color

3.1.1 Definition

Color is a perception that depends on the response of the human visual system to light and the interaction of light with objects. It is a product of the illuminant, surface spectral reflectance and sensor sensitivity (i.e. of digital sensors or of cones in the human eye). Color is one of the most widely used visual features in content-based image retrieval. It is relatively robust to background complication and independent of image size and orientation. The key issues in color feature extraction include the color space, color quantization, and the choice of similarity function. Various studies of color perception and color spaces have been proposed [8] [9] [10]. Each pixel of the image can be represented as a point in a 3D color space. If we want to describe an image by its color features, we have to first determine the color space to use. There exist different space models such as RGB, HSV, CIE L*a*b*, CIE L*u*v* or opponent color. The best representation depends on the special needs of the application.

3.1.2 Color space

There are a number of different color spaces currently used for the representation of images in the digital world. Choosing an appropriate color space for the implementation of a content based image retrieval system is not only important to the production of the accurate results, but to the accurate representation of color in the way that the human visual system perceives it. There are a number of color spaces in use of which some of the most commonly used are:

3.1.2.1 RGB

The most popular color space is RGB which stands for Red-Green-Blue. This space consists of the additive primary colors of light Red, Green and Blue. Varying levels of the three colors are added to produce more or less any color in the visible spectrum. This space is device dependant and perceptually non-uniform. This means that a color relative close together in the RGB space may not necessarily be perceived as being close by the human eye. RGB space is normally used in Cathode Ray Tube (CRT) monitors, television, scanners, 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 as in Fig 2.

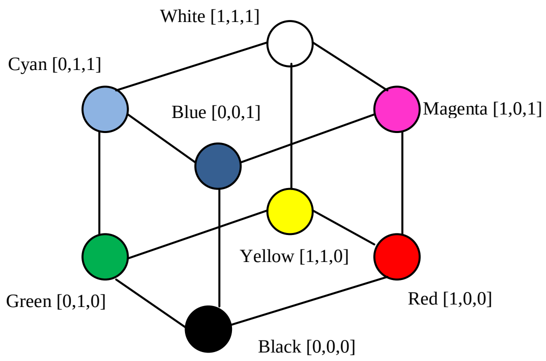

Fig 2: RGB Color space

3.1.2.2 HSV

Colors in the HSV color space are defined in terms of three constituent components; Hue, Saturation and Value. Hue is the type of color (red, blue, etc), saturation is the vibrancy of the color (the lower the saturation the more grayness is present) and the value is the brightness of the color. HSV is again a device dependant representation and is defined relative to the RGB color space. RGB coordinates can be easily translated to the HSV coordinates by a simple formula. HSV is perceptually uniform so colors close in value are also perceived close by the human eye. HSV space is widely used in computer graphics, especially in the interfaces of the applications where the user browse the color space to select an instance of a color.

3.1.2.3 The Opponent Color Space

There is evidence that human color vision uses an opponent-color model by which certain hues were never perceive to occur together. For example, a color perception is never described as redish-greens or bluish-yellows, while combinations of red and yellow, red and blue, green and yellow, and green and blue are readily perceived. Based on this observation, the opponent color space is proposed to encode the color into opponent signal. This is separated into three components defined from the RGB values (R-G, 2B-R-G, R+B+G). Such type representation has the advantage of isolating the brightness information on the third channel.

*3.1.2.4 CIE L*a*b* and CIE L*u*v**

CIE L*a*b* and CIE L*u*v*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. CIE L*u*v* was an attempt to linearize the perceptibility of the color differences.

3.1.3 Methods of representation

Each feature may have several representations. For example, color histograms [8], color moments [11], color or color correlograms [12] coherence vectors [13], etc are representations of the image color feature. Moreover, numerous variations of the color histogram itself have been proposed, each of which differs in the selected color-quantization scheme. The color descriptors are related to mathematical operations of the pixel values represented in a certain color space. Some of the most popular descriptors are:

3.1.3.1 Color histogram
The main method of representing color information of images in CBIR systems is through color histograms [8]. 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. The most common form of the histogram is obtained by splitting the range of the data into equally sized bins. 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. One of the main drawbacks of the color histogram is that it does not take into consideration the spatial information of pixels. Thus very different images can be considered similar because they have similar color distributions. An improvement of the color histogram method includes the cumulated color histogram [11], proposed by Stricker and Orengo. Their results demonstrated the advantages of the proposed approach over the conventional color histogram approach. However the approach has the disadvantage that in case of more than one dimensional histograms, there is no clear way to order bins.

3.1.3.2 Color Moments
To avoid the quantization drawbacks, Stricker and Orengo proposed using the color moments approach [11]. 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 suffer from the problem that they 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.

3.1.3.3 Color Correlogram
Jing Huang et al propose the color correlogram [12] as a means of encoding the color information of an image. This method, unlike color histograms and moments, incorporates spatial data in the encoded color information and therefore avoids a number of the problems of those representations. The color correlogram has the advantages that t includes the spatial correlation of colors, can be used to describe the global distribution of local spatial correlation of colors and is simple to compute.

3.1.3.4 Color coherence vector
A color coherence vector [13] 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 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 CIE L*u*v* and CIE L*a*b* space.

3.2 Texture

3.2.1 Definition
Texture refers to the visual patterns that have properties of homogeneity that do not result from the presence of only a single color or intensity. It is a natural property of virtually all surfaces, including clouds, trees, bricks, hair, and fabrics. It contains important information about the structural arrangement of surfaces and their relationship to their surrounding environment. Fig 3 shows a few types of textures.

Fig 3. Examples of Texture

3.2.2 Methods of representation
Texture representation methods can be classified into three categories:

- *Statistical techniques* characterize texture using the statistical properties of the gray levels of the pixels comprising an image. Normally, in images, there is periodic occurrence of certain gray levels. The spatial distribution of gray levels is calculated.
- *Structural techniques* characterize texture as being composed of texels (texture elements). These texels are arranged regularly on a surface according to some specific arrangement rules.
- *Spectral techniques* are based on properties of the Fourier spectrum and describe global periodicity of the grey levels of a surface by identifying high-energy peaks in the Fourier spectrum.

Statistical techniques are most important for texture classification because it is these techniques that result in computing texture properties. Some of the statistical representations of texture are tamura features, co-occurance matrices, and multi-resolution filtering techniques such as Gabor and wavelet transform.

3.2.2.1 Tamura Features
Motivated by the psychological studies in human visual perception of texture, Tamura et al. explored the texture representation from a different angle (14). They developed computational approximations to the visual texture properties found to be important in psychological studies. The six visual texture properties are coarseness, contrast, directionality, linelikeness, regularity and roughness. Since the texture properties are visually meaningful, these features are very attractive in image retrieval systems. This way, the user can use a verbal description of the image end texture properties can be represented in a user-friendly interface. Directionality, contrast and coarseness were used in some early retrieval systems like directionality were accepted as the texture browsing descriptor included in the MPEG-7 standard [15].

3.2.2.2 Co-occurrence matrices
Co-occurance matrix was originally proposed by R.M. Haralick [19]. This technique constructs a co-occurance

matrix on the basis of orientation and the distance between the pixels. Then meaningful statistics are extracted from matrix as the texture representation. Many other researchers followed the same line and further proposed enhanced versions. For example, Gotlieb and Kreyszig studied the statistics originally proposed in [16] and experimentally found out that contrast, inverse deference moment, and entropy had the biggest discriminatory power [17].

3.2.2.3 Gabor filters

Gabor filters consists of a group of wavelets each of which capturing energy at a specific resolution and orientation. Therefore, Gabor filters are able to capture the local energy of the entire signal or image. The Gabor filter has been widely used to extract image features, especially texture features [18]. Daugman discovered that Gabor filters provide optimal Heisenberg joint resolution in visual space and spatial frequency. For this reason, Gabor filters have been successfully employed in many applications including image coding, texture segmentation, retina identification, document analysis, target detection, fractal dimension measurement, line characterization, edge detection, image representation, and others.

3.2.2.4 Wavelet Transform

Another multi-resolution approach, wavelet transforms, have been used most widely in many aspects of image processing. A wide range of wavelet-based tools and ideas have been proposed and studied for noise removal from images, image compression, image reconstruction, and image retrieval. The multi-resolution wavelet transform has been employed to retrieve images in [19]. The wavelet features do not achieve high level of retrieval accuracy. Therefore, various methods have been developed to achieve higher level of retrieval accuracy using wavelet transform. Wavelet features computed from discrete wavelet coefficients are assigned weights to increase effectiveness in CBIR [8].

3.3 Shape

3.3.1 Definition

Defining the shape of an object is often very difficult. 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.

3.3.2 Methods of representation

Two major steps are involved in shape feature extraction. They are object segmentation and shape representation. Once objects are segmented, their shape features can be represented and indexed. In general, shape representations can be divided into two categories, boundary-based and region-based (Fig 4). The former uses only the outer boundary of the shape while the latter 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 these two categories are Fourier descriptors and moment variants. The main idea of Fourier Descriptor is to use the Fourier transformed boundary as the shape feature [20] [21] whereas moment invariants is to use region-based moments, which are invariant to transformations as the shape feature. In [22], Hu identified seven such moments.

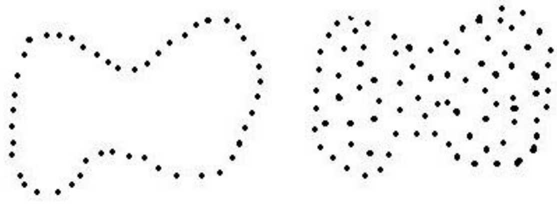

Fig 4: Boundary-based & Region-based shape representations

4. User Interfaces for CBIR Systems

Here focus lies in the design and implementation of an algorithm for the purpose of content based image retrieval, however a suitable user interface is required to interact with the algorithm. The user interface will be essential to simplify the process of testing and evaluation of Content Based Image Retrieval. It is useful to include extra features allowing the selection of the retrieval algorithm to be used and the display of graphs or other means to view a mathematical analysis of the quality of results.

Graphical User Interface (GUI) is created using a tool called GUIDE, the GUI Development Environment in Matlab. It allows simple and intuitive ways of browsing capabilities, where the user navigates through the database entries by simply clicking on the thumbnail images presented to him. These thumbnail images are retrieved based on their similarity to the image the user clicks on. This tool allows a programmer to layout the GUI, selecting and aligning the GUI components to be placed in it. Once the components are in place, the programmer can edit their properties: name, color, size, font, text to display, and so forth. The GUI after applying the query image is shown in Fig 5. It contains commands for 'Open Image', 'Retrieve', 'Save', 'Delete', 'Cancel', 'Exit', etc. Fig 5 shows GUI after applying the query image.

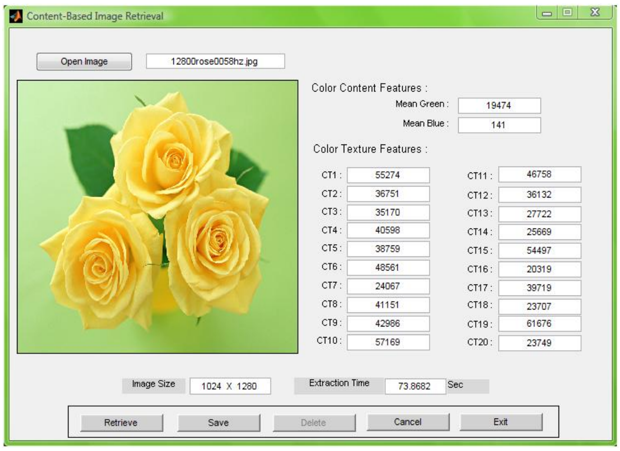

Fig 5: Graphical User Interface (GUI)

5. Similarity Measurement

The 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. Finding good similarity measures between images based on some feature set 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. 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. Many distance measures can be applied to evaluate the similarity of two images according to their features [10]. 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:

5.1 Minkowski-Form distance

The Minkowski-Form distance is the most widely used metric for image retrieval. Given two feature vectors f_1 and f_2 of N bins, this measure is defined as follows

$$D(f_1, f_2) = (\sum_1^N |f_1(i) - f_2(i)|^p)^{1/p}$$

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∞).

5.2 Euclidean Distance

Euclidean distance 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

$$D = \sqrt{\sum_{k=1}^{n}(p_k - q_k)^2}$$

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. For instance, MARS system [23] used Euclidean distance to compute the similarity between texture features; Netra [24] used Euclidean distance for color and shape feature; Blobworld [25] used Euclidean distance for texture and shape feature.

5.3 Manhattan distance

If the Euclidean distance is considered as the straight line distance between points then the Manhattan distance 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

$$D = \sum_{k=1}^{n} |p_k - q_k|$$

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

6. Applications of CBIR

A wide range of possible applications for CBIR technology has been identified. Some of these are listed below:

- Criminal investigations: automatic face recognition systems, copyright violation on the Internet
- Shapes recognition: identification of parts, defect and fault inspection in industrial automation
- Medical diagnosis: Tumors detection, medical imaging measurement of internal organs
- Journalism and advertising
- Remote sensing: geographical information systems, weather forecast, monitoring of satellite images.
- Fashion, graphic design, advertising
- Trademark databases
- Architectural and engineering design
- Art galleries, museums, archaeology
- Image search on the Internet
- Cartography: map making from photographs, synthesis of weather maps.
- Digital Forensics: finger print matching and analysis of security systems crime detection.
- Radar engineering: detection and identification of targets, guidance of aircraft and missiles
- Robotics: motion control through visual feedback, recognition of objects in a scene

7. Conclusion and Future Scope of Work

The area of content-based image retrieval is a hybrid research area that requires knowledge of both computer vision and of database systems. The application of information theory to image interpretation and CBIR poses many questions for further exploration. The technology is exciting but immature, and few operational image archives have yet shown any serious interest in adoption. The field appears to be generating interesting and valid results, even though it has so far led to few commercial applications. Agencies concerned with technology transfer or dissemination of best practice in fields which could potentially benefit from CBIR (including management of image collections and drawing archives, electronic publishing and multimedia content creation) should consider sponsoring programmes to raise awareness of CBIR technology among leading practitioners in these fields.

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