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Image Retrieval a Sophisticated method

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Abstract— Image retrieval is one of the main topics in the field of computer vision and pattern recognition. In the early 1990s, researchers have built many image retrieval systems, such as QIBC, MARS, FIDS and so on. They are different from the traditional image retrieval systems. These systems are based on image features such as color, texture, shape of objects and so on. Nowadays, the main research work of image retrieval consists of feature extracting techniques, image similarly match and image retrieval methods. Many researchers have put forward various algorithms to extract color, texture and shape features. Color is the most dominant and distinguishing visual feature. Color histogram-based techniques re-main popular due to their simplicity, but it lacks spatial information. Several color descriptors try to incorporate spatial information to varying degrees, it include the compact color moments, color coherence vector and color correlograms[1]. Texture is used to specify the roughness or coarseness of object surface and described as a pattern with some kind of regularity. Many researchers have put forward various algorithms for texture analysis, such as the gray co-occurrence matrixes, Markovrandom field (MRF) model, simultaneous auto-regressive (SAR) model, Wold decomposition model, Gabor filtering and wavelet de-composition and so on. Shape features are widely used in various areas such as object recognition and content-based image retrieval.

The classic methods of describing shape features are moment invariants, Fourier trans-form coefficients, edge curvature and arc length. Various methods are put forwarded by many researchers to integrate color, texture and shape features for efficient image retrieval.

The need for efficient content based image retrieval(CBIR) has increased tremendously in many applications areas such as biomedicine, military, commerce, education, and web image classification and searching. CBIR is highly challenging because of the large size of the database, the difficulty of understanding images, both by people and computers, the difficulty of formulating a query, and the problem of evaluating the results. Efficient indexing and searching of large-scale image data bases remain as an open problem. The automatic derivation of semantics from the content of an image is the focus of interest of the present research on image databases.

One of the powerful and significant visual primitive that concisely describe image content is the texture. Texture analysis and characterization was widely studied over the last three decades in a variety of applications, including medical imaging, remote sensing, pattern recognition, industrial inspection and texture based image retrieval. Texture plays a significant role for the last few decades in various fields of image processing and pattern recognition.

Many researchers developed various texture based methods for image classification, recognition, segmentation, analysis, for finding abnormalities and future analysis on medical images, remote sensing and image retrieval etc. There is no unique definition for texture. The present research understands that texture is not only defined by the grey level value or intensity of that pixel but it is defined and measured by the surrounding or neighboring pixel grey level or with any other common property of those pixels.

Image retrieval means retrieving or identifying the correct image from the pool of the image database. Most of the times a part of the image will be given as test image and the method should retrieve the exact image that part belongs. To address this problem the present research adopts various methods based on texture properties. It is proposed to derive new image Retrieval method by analyzing local properties of part of image based on the features of the texture.

KEYWORDS: Image, shape, colour, texture Shape, LBP

I. INTRODUCTION

1.1 The Growth of Digital Imaging

The twentieth century has witnessed unparalleled growth in the number, availability and importance of images in all walks of life. Images now play a crucial role in fields as diverse as medicine, journalism, advertising, design, education, entertainment, etc. Technology, in the form of inventions such as photography and television, has played a major role in facilitating the capture and communication of image data. But the real engine of the imaging revolution has been the computer, bringing with it a range of techniques for digital image capture, processing, storage and transmission through internet. The creation of the World-Wide Web in the early 1990s, enabling users to access data in a variety of media from anywhere on the planet, has provided a further massive stimulus to the exploitation of digital images. The number of images available on the web was recently estimated to be between 10 to 30 million [65], which some observers consider to be a significant underestimate.

The process of digitization does not itself make image collections easier to manage. The need for efficient storage and retrieval of images recognized by managers of large image collections such as picture libraries and design archives for many years was reinforced by a workshop sponsored by the USA's National Science Foundation in 1992 [31]. Problems with traditional methods of image indexing [13] 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 in a technology now generally referred to as Content Based Image Retrieval (CBIR). The CBIR systems allow the user to iteratively search image databases looking for those images which are similar to a specified query image. Selection and ranking of relevant images from image collections remains a problem in CBIR. Image retrieval has been an active research topic in recent years due to its potentially large impact on both image understanding and Web image search. There is a growing interest in CBIR because of the limitations inherent in metadata based systems, as well as the large range of possible uses for efficient image retrieval.

1.2 Content Based Image Retrieval (CBIR) Systems

The earliest use of the term CBIR in the literature seems to have been by Kato [35], to describe his experiments into automatic retrieval of images from a database by color and shape feature. The term CBIR has since been widely used to describe the process of retrieving desired images from a large collection on the basis of features (such as color, texture and shape) that can be automatically extracted from the images themselves. The features used for retrieval can be either primitive or semantic, but the extraction process must be predominantly automatic. Retrieval of images by manually assigned keywords is definitely not CBIR as the term is generally understood even if the keywords describe image content.

CBIR differs from classical information retrieval in that image databases are essentially unstructured, since digitized images consist purely of arrays of pixel intensities, with no inherent meaning. One of the key issues with any kind of image processing is the need to extract useful information from the raw data (such as recognizing the presence of particular shapes or textures) before any kind of reasoning about the image's contents is possible. Image databases thus differ fundamentally from text databases, where the raw material (words stored as ASCII character strings) has already been logically structured by the author [63]. There is no equivalent of level one retrieval in a text database.

CBIR draws many of its methods from the field of image processing and computer vision, and is regarded by scholars as a subset of that field. It differs from these fields principally through its emphasis on the retrieval of images with desired characteristics from a collection of significant size. Image processing covers a much wider field, including image enhancement, compression, transmission, and interpretation. While there are grey areas (such as object recognition by feature analysis), the distinction between mainstream image analysis and CBIR is usually fairly clear cut. An example may make this clear. Many police forces now use automatic face recognition systems. Such systems may be used in one of two ways. Firstly, the image in front of the camera may be compared with a single individual's database record to verify his or her identity. In this case, only two images are matched, a process few observers would call CBIR. Secondly, the entire database may be searched to find the most closely matching images. This is a genuine example of CBIR.

Research and development issues in CBIR cover a range of topics, many shared with mainstream image processing and information retrieval. Some of the most important are:

Understanding image users' needs and information-seeking behavior.

Identification of suitable ways of describing image content.

Extracting features from raw images.

Providing compact storage for large image databases.

Matching query and stored images in a way that reflects human similarity judgments.

Efficiently accessing stored images by content.

Providing usable human interfaces to CBIR systems.

The general block diagram of a typical CBIR system is given in Fig. 1.1. Generally speaking, image content may include both visual and semantic content. Visual content can be very general or domain specific. General visual content include color, texture, shape, spatial relationship, etc. Domain specific visual content, like human faces, is application dependent and may involve domain knowledge. Semantic content is obtained either by textual annotation or by complex inference procedures based on visual content. A good visual content descriptor should be invariant to the accidental variance introduced by the imaging process (e.g., the variation of the illuminant of the scene).

Content based image retrieval uses the visual contents of an image such as color, shape, texture, and spatial layout to represent and index the image. In typical CBIR systems as shown in Fig.1.1, the visual contents of the images in the database are extracted and described by multidimensional feature vectors. The feature vectors of the images in the database form a feature database. To retrieve images, users provide the retrieval system with example images or sketched figures. The system then changes these examples into its internal representation of feature vectors. The similarities/distances between the feature vectors of the query example or sketch and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme. The indexing scheme provides an efficient way to search for the image database. Recent retrieval systems have incorporated users' relevance feedback to modify the retrieval process in order to generate perceptually and semantically more meaningful retrieval results.

1.3 General Visual Content Descriptor for CBIR System

1.3.1 Color Space

Color is the most extensively used visual content for image retrieval [16, 27, 28, 29, 32, 44, 49, 72, 73, 86]. Its three-dimensional values make its discrimination potentiality superior to the single dimensional gray values of images. Before selecting an appropriate color description, color space must be determined first. Each pixel of the image can be represented as a point in a 3D color space. Commonly used color space for image retrieval include RGB, Munsell, CIE L*a*b*, CIE L*u*v*, HSV (or HSL, HSB), and opponent color space. There is no agreement on which is the best. However, one of the desirable characteristics of an appropriate color space for image retrieval is its uniformity [44]. Uniformity means that two color pairs that are equal in similarity distance in a color space are perceived as equal by viewers. In other words, the measured proximity among the colors must be directly related to the psychological similarity among them.

RGB space is a widely used color space for image display. It is composed of three color components red, green, and blue. These components are called "additive primaries" since a color in RGB space is produced by adding them together. In contrast, CMY space is a color space primarily used for printing. The three color components are cyan, magenta, and yellow. These three components are called "subtractive primaries" since a color in CMY space is produced through light absorption. Both RGB and CMY space are device-dependent and perceptually non-uniform.

The CIE L*a*b* and CIE L*u*v* spaces are device independent and considered to be perceptually uniform. They consist of a luminance or lightness component (L) and two chromatic components a and b or u and v. The transformation of RGB space to CIE L*u*v* or CIE L*a*b* space can be found in [32].

The HSV (or HSL, or HSB) space is widely used in computer graphics and is a more intuitive way of describing color. The three color components are hue, saturation (lightness) and value (brightness). The hue is invariant to the changes in illumination and camera direction and hence more suited to object retrieval. RGB coordinates can be easily translated to the HSV (or HLS, or HSB) coordinates [16]. The opponent color space uses the opponent color axes (R-G, 2B-R-G, R+G+B). This representation has the advantage of isolating the brightness information on the third axis. With this solution, the first two chromaticity axes, which are invariant to the changes in illumination intensity and shadows, can be down-sampled since humans are more sensitive to brightness than they are to chromatic information.

1.3.2 Texture

Texture is one of the crucial primitives in human vision and texture features have been used to identify content of images. Texture is the term used to characterize the surface of a given object or phenomenon. It is undoubtedly one of the main features used in image processing, pattern recognition and multispectral scanner images obtained from aircraft or satellite platforms for microscopic images of cell cultures or tissue samples. Texture also plays an important role in human visual perception, medical image processing, content retrieval systems and provides information for recognition and interpretation [42]. One crucial distinction between color and texture features is that color is a point or pixel property, whereas texture is a local-neighborhood property. As a result, it does not make any sense to discuss the texture content at pixel level without considering the neighborhood.

1.3.3 Shape

Shape features of objects or regions have been used in many content-based image retrieval systems [17, 21, 30, 74]. Compared with color and texture features, shape features are usually described after images have been segmented into regions or objects. Since robust and accurate image segmentation is difficult to achieve, the use of shape features for image retrieval has been limited to special applications where objects or regions are readily available. The state-of-art methods for shape description can be categorized into either boundary-based (rectilinear shapes [30], polygonal approximation [3], finite element models [66], and Fourier-based shape descriptors [2, 36, 50]) or region-based methods (statistical moments [26, 85]). A good shape representation feature for an object should be invariant to translation, rotation and scaling.

1.4 Literature Survey

There has been a lot of interest in content-based image retrieval using visual features over the last decade. An overview of work in this area can be found in [11, 20, 40, 62, 69, 80, 81]. CBIR is like an information filter process and is expected to provide a high percentage of relevant images in response to user query [4]. It should conform to human perception of visual semantics. In general, the image features tend to capture only some of the aspects of image similarity and hence it becomes difficult to clearly specify what or how a user should initiate queries. The presence of large volumes of digital repositories leads to many schemes of indexing and retrieval of such data (e.g.,QBIC [15, 46], Netra [41], VisualSeek [68], Chabot [47], Blobworld [6], etc). In all these cases, the user is interested in seeking the most similar images to his query.

Gudivada et al. [22] have identified many important applications of general purpose CBIR. The CBIR has been applied for many purposes [37] in law enforcement and crime prevention, such as fingerprint recognition [60], face recognition [43], DNA matching, shoe sole impressions [18], and surveillance systems [8]. Integrated tools in Web image retrieval can help considerably in identifying suspicious sites and thus in filtering them. This can be done by submitting suitable sample queries to a query-based retrieval system, which tries to identify all Web pages that correspond to them. Wang et al. [84], for example, designed a system called IBCOW that classifies Web sites into “objectionable” and “benign” based on image content.

Color is one of the most important image indexing features employed in CBIR. Schettini et al. [64] and Del Bimbo [11] provide a comprehensive survey of various methods employed for color image indexing and retrieval in image databases. Some of the popular methods to characterize color information in images are color histograms [23, 73], color moments [71], and color correlograms [27]. Though all these methods provide good characterization of color, they have the problem of high-dimensionality. This leads to more computational time, inefficient indexing, and low performance. To overcome these problems, use of SVD [23], dominant color regions approach [61, 86], and color clustering [34, 83] have been proposed. The work in [1] presents a scheme for indexing and retrieval of color image data. In [9], a signature bit string representation for color feature is used. The proposal of using variable number of color histograms for color representation, depending on number of colors in the image is discussed in [70]. It is shown to be better than using global histograms. In [38], a flexible sub-block image retrieval algorithm robust to translation, lighting change, and object appearance is proposed.

Shape is an important feature for perceptual object recognition and classification of images. Many authors have done a survey of various shape methods used for content-based image retrieval [11, 19, 81, 82]. Recently, techniques using shape measure as an important feature have been used for CBIR. Features such as moment invariants and area of region have been used in [15, 45, 53], but do not give perceptual shape similarity. Cortelazzo et al. [10] used chain codes for trademark image shape description and string matching technique. The chain codes are not normalized and string matching is not invariant to shape scale. Jain and Vailaya [33] proposed a shape representation based on the use of a histogram of edge directions. In [52] it is shown that applying shape-based indexing of color images using a similar grid-based representation as in [39,83], but different indexing and similarity measures, better retrieval results are obtained for color image regions. Further, along with color, shape is added as an additional feature to index the extracted regions within the images. A retrieval system using combined color and shape indexing where query is cascaded by color and then shape has been developed [51]. This combines the earlier grid-based shape representation with the dominant color-based index to provide better retrieval efficiency and effectiveness. Most of the recent approaches like [14, 71] advocate the method of dividing the image space into sub-blocks and use the features extracted out of each sub block to index the whole image on those features.

Region-based retrieval systems attempt to overcome the issues of color layout search by representing images at the object-level. A region-based retrieval system [41] applies image segmentation to decompose an image into regions, which correspond to objects if the decomposition is ideal. Since the retrieval system has identified objects in the image, it is easier for the system to recognize similar objects at different locations and with different orientations and sizes. Region-based retrieval systems include the NeTra system [41], the Blobworld system [7], and the query system with color region templates [67].

Analysis of texture, which is an essential part of any CBIR system, requires the identification of features that differentiate the textures in the image for segmentation, classification and recognition. The texture features are one of the important features for an efficient and cost effective retrieval system. Many texture features derived from various approaches of texture analysis and classification are thus important and crucial to build an efficient retrieval system [5, 8, 24, 42, 55, 56, 57, 58, 59, 75, 76, 77, 78, 79].

Some low-level feature, techniques for matching similarity are derived recently [48].These techniques are efficient for browsing systems by exploiting semantics. A similarity measure applicable to flexible feature signatures with respect to their qualities of effectiveness and efficiency's is proposed for determining similarities among data objects, which is a core task of content-based multimedia retrieval systems [54].Recently image retrieval methods based on shape is analyzed, compared and based on this a relevance feedback is also introduced [25]. A single-loop approach that computes both the mean and the standard deviation in a single pass is vectorized, over the optimized scalar implementations of content based image retrieval.

II. REFERENCES

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