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Content Based Image Retrieval by Gray Level Conversion

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***Abstract:** Content Based Image Retrieval is an interesting and most emerging field in the area of 'Image Search', finding similar images for the given query image from the image database. Current approaches include the use of color, texture and shape information. Considering these features in individual, most of the retrievals are poor in results and sometimes we are getting some non relevant images for the given query image.*

So, in this seminar a method in which combination of color and texture features of the image is used to improve the retrieval results in terms of its accuracy. For color, color histogram based color correlogram technique and for texture wavelet decomposition technique is implemented. In Content Based Image Retrieval, color and texture based image retrieval computes image features automatically from a given query image and these are used to retrieve images from database more efficiently

Keywords: Content-based image retrieval, Color histogram system, Histogram attributed relational graphs, Histogram image retrieval.

I. INTRODUCTION

Interest in the potential of digital images has increased enormously over the last few years, fuelled at least in part by the rapid growth of imaging on the World-Wide Web. Users in many professional fields are exploiting the opportunities offered by the ability to access and manipulate remotely-stored images in all kinds of new and exciting ways. However, they are also discovering that the process of locating a desired image in a large and varied collection can be a source of considerable frustration. The problems of image retrieval are becoming widely recognized, and the search for solutions an increasingly active area for research and development.

Problems with traditional methods of image indexing 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** (CBIR). However, the technology still lacks maturity, and is not yet being used on a significant scale. In the absence of hard evidence on the effectiveness of CBIR techniques in practice, opinion is still sharply divided about their usefulness in handling real-life queries in large and diverse image collections.

The aim of this report is to clarify some of the issues raised by this new technology, by reviewing its current capabilities and limitations, and its potential usefulness to users in higher education and elsewhere. The need to find a desired image from a collection is shared by many professional groups, including journalists, design engineers and art historians. While the requirements of image users can vary considerably, it can be useful to characterize image queries into three levels of abstraction: primitive features such as color or shape, logical features such as the identity of objects shown, and abstract attributes such as the significance of the scenes depicted. While CBIR systems currently operate effectively only at the lowest of these levels, most users demand higher levels of retrieval.

II. LITERATURE REVIEW

2.1 History

Several reviews of the literature on image retrieval have been published, from a variety of different viewpoints. Enser [1995] reviews methods for providing subject access to pictorial data, developing a four-category framework to classify different approaches. He discusses the strengths and limitations both of conventional methods based on linguistic cues for both indexing and search, and experimental systems using visual cues for one or both of these. His conclusions are that, while there are serious limitations in current text-based techniques for subject access to image data, significant research advances will be needed before visually-based methods are adequate for this task. He also notes, as does Cawkell [1993] in an earlier study, that more dialogue between researchers into image analysis and information retrieval is needed. CBIR techniques are likely to be of most use in restricted subject domains, and where synergies with other types of data (particularly text and speech) can be exploited.

Eakins [1996] proposes a framework for image retrieval (outlined in section **Error! Reference source not found.** above), classifying image queries into a series of levels, and discussing the extent to which advances in technology are likely to meet users' needs at each level. His conclusion is that automatic CBIR techniques can already address many of users' requirements at level 1, and will be capable of making a significant contribution at level 2 if current research ideas can be successfully exploited. They are however most unlikely to make any impact at level 3 in the foreseeable future.

Idris and Panchanathan [1997a] provide an in-depth review of CBIR technology, explaining the principles behind techniques for color, texture, shape and spatial indexing and retrieval in some detail. De Marsicoi et al [1997] also review current CBIR technology, providing a useful feature-by-feature comparison of 20 experimental and commercial systems. In addition to these reviews of the literature, a survey of "non-text information retrieval" was carried out in 1995 on behalf of the European Commission by staff from GMD (Gesellschaft fur Mathematik and Datenverarbeitung), Darmstadt and Universite Joseph Fourier de Grenoble [Berrut et al, 1995].

III. WHAT IS CBIR?

The earliest use of the term *content-based image retrieval* in the literature seems to have been by Kato [1992], to describe his experiments into automatic retrieval of images from a database by color and shape feature. The term 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. 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 [Santini and Jain, 1997]. There is no equivalent of level 1 retrieval in a text database.

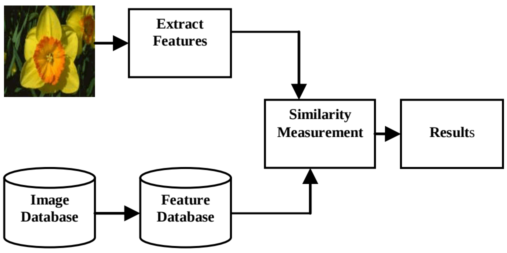


Fig.3: Block diagram of the system

Retrieval Procedure

In gray level conversion CBIR system consists of two major parts. The first one is feature extraction, where a set of features is generated to represent the content of each image in the database. The second task is similarity measurement, where a distance between the query image and each image in the database is computed using their feature vectors so that the most similar images can be retrieved. The block diagram of the system is presented in Figure 3.

3.1 Content Based Techniques

There are some common methods for extracting content from images so that they can be easily compared. The methods outlined are not specific to any particular application domain.

3.1.1 Color Retrieval

Color is the most extensively used visual content for image retrieval. 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. Retrieving images based on color similarity is achieved by computing a color histogram for each image that identifies the proportion of pixels within an image holding specific values. The first order (mean), the second order (variance) and the third order (skew ness) color moments have been proved to be efficient and effective in representing color distributions of images.

A different way of incorporating spatial information into the color histogram, color coherence vectors (CCV), was proposed. Each histogram bin is partitioned into two types, i.e., coherent, if it belongs to a large uniformly-colored region, or incoherent, if it does not. Another method called color correlogram expresses how the spatial correlation of pairs of colors changes with distance.

An example of a color histogram in the HSV color space can be seen with the following image:

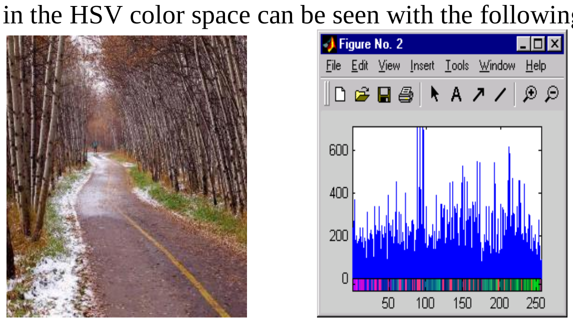
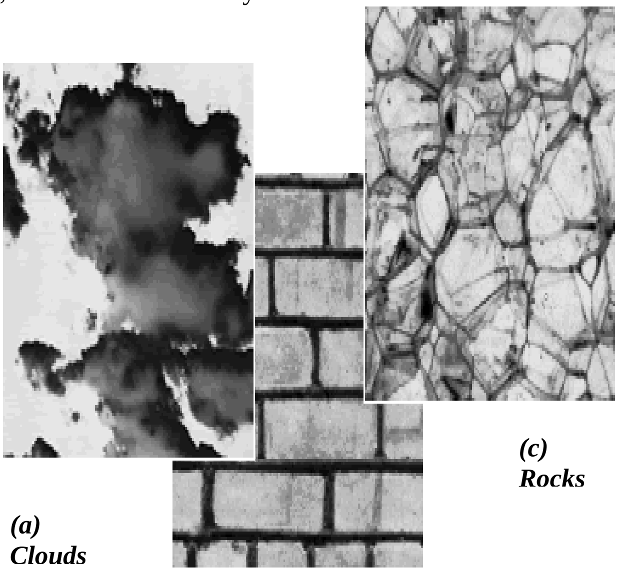


Fig.3.1.1: Color histogram in the image

3.1.2 Texture Retrieval

Texture is a widely used and intuitively obvious but has no precise definition due to its wide variability. Visual texture in most cases is defined as a repetitive arrangement of some basic pattern. This repetition may not be random. However, a texture pattern normally has some degree of randomness due to randomness in basic pattern as well as due to randomness in the repetition of basic pattern. To quantify texture, this randomness is measured by some means over a small rectangular region called window. Thus, texture in an image turns out to be a local property and depends on the shape and size of the window. Identifying a patch in an image as having uniform texture or discriminating different visual textures obeys the law of similarity. In this case, the texture property is used to produce similarity groupings.

Basically, texture representation methods can be classified into two categories: *structural* and *statistical*. Structural methods, including *morphological operator* and *adjacency graph*, describe texture by identifying structural primitives and their placement rules. They tend to be most effective when applied to textures that are very regular. Statistical methods, including Fourier power spectra, co-occurrence matrices, shift-invariant principal component analysis (SPCA), Tamura feature, Wold decomposition, Markov random field, fractal model, and multi-resolution filtering techniques such as Gabor and wavelet transform, characterize texture by the statistical distribution of the image intensity.



(c) Rocks

(a) Clouds

(b) Bricks

Fig.3.1.2: Different types of texture

3.1.3 Shape Retrieval

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.

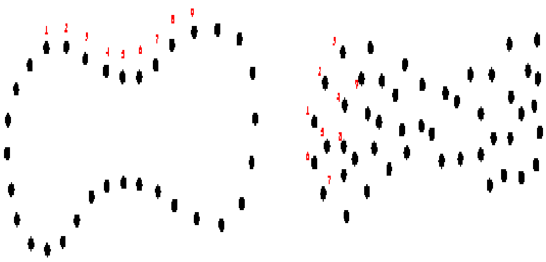


Fig.3.1.3: Boundary-based & Region-based shape representation

IV. RETRIEVAL BY OTHER TYPES OF PRIMITIVE FEATURE

One of the oldest-established means of accessing pictorial data is retrieval by its position within an image. Accessing data by spatial location is an essential aspect of geographical information systems and efficient methods to achieve this have been around for many years (e.g. Chock et al [1984], Roussopoulos et al [1988]). Similar techniques have been applied to image collections, allowing users to search for images containing objects in defined spatial relationships with each other (Chang et al [1988], Chang and Jungert [1991]). Improved algorithms for spatial retrieval are still being proposed [Gudivada and Raghavan, 1995b]. Spatial indexing is seldom useful on its own, though it has proved effective in combination with other cues such as colour (Stricker and Dimai [1996], Smith and Chang [1997a]) and shape [Hou et al, 1992]. Several other types of image feature have been proposed as a basis for CBIR. Most of these rely on complex transformations of pixel intensities which have no obvious counterpart in any human description of an image. Most such techniques aim to extract features which reflect some aspect of image similarity which a human subject can perceive, even if he or she finds it difficult to describe. The most well-researched technique of this kind uses the *wavelet transform* to model an image at several different resolutions.

V. CURRENT TECHNIQUES FOR IMAGE RETRIEVAL

5.1Exact Matching – This category is applicable only to static environments or environments in which features of the images do not evolve over an extended period of time. Databases containing industrial and architectural drawings or electronics schematics are examples of such environments.

5.2 Low-Level Similarity-Based Searching In most cases, it is difficult to determine which images best satisfy the query. Different users may have different needs and wants. Even the same user may have different preferences under different circumstances. Thus, it is desirable to return the top several similar images based on the similarity measure, so as to give users a good sampling. The similarity measure is generally based on simple feature matching and it is quite common for the user to interact with the system so as to indicate to it the quality of each of the returned matches, which helps the system adapt to the users' preferences. Figure 1 shows three images which a particular user may find similar to each other. In general, this problem has been well-studied for many years.

5.3 High-Level Semantic-Based Searching In this case, the notion of similarity is not based on simple feature matching and usually results from extended user interaction with the system. Figure 2 shows two images whose low-level features are quite different, yet could be semantically similar to a particular user as examples of peaceful scenes. Research in this area is quite active, yet still in its infancy. Many important breakthroughs are yet to be made.

VI. AVAILABLE CBIR SOFTWARE

Despite the shortcomings of current CBIR technology, several image retrieval systems are now available as commercial packages, with demonstration versions of many others available on the Web. Some of the most prominent of these are described below.

Commercial systems *QBIC.* IBM's QBIC[i] system [Flickner et al, 1995] is probably the best-known of all image content retrieval systems. It offers retrieval by any combination of color, texture or shape – as well as by text keyword. Image queries can be formulated by selection from a palette, specifying an example query image, or sketching a desired shape on the screen. The system extracts and stores color, shape and texture features from each image added to the database, and uses R*-tree indexes to improve search efficiency at search time, the system matches appropriate features from query and stored images, calculates a similarity score between the query and each stored image examined, and displays the most similar images on the screen as thumbnails.

***Virage*.** Another well-known commercial system is the VIR Image Engine from Virage, Inc [Gupta et al, 1996]. This is available as a series of independent modules, which systems developers can build in to their own programs. This makes it easy to extend the system by building in new types of query interface, or additional customized modules to process specialized collections of images such as trademarks. Alternatively, the system is available as an add-on to existing database management systems such as Oracle or Informix.

VII. EXPERIMENTAL SYSTEMS

A large number of experimental systems have been developed, mainly by academic institutions, in order to demonstrate the feasibility of new techniques. Many of these are available as demonstration versions on the Web. Some of the best-known are described below.

7.1 Photo-book. The Photo-book system [Pentland et al, 1996] from Massachusetts Institute of Technology (MIT) has proved to be one of the most influential of the early CBIR systems. Like the commercial systems above, aims to characterize images for retrieval by computing shape, texture and other appropriate features. Unlike these systems, however, it aims to calculate *information-preserving* features, from which all essential aspects of the original image can in theory be reconstructed. This allows features relevant to a particular type of search to be computed at search time, giving greater flexibility at the expense of speed. The system has been successfully used in a number of applications, involving retrieval of image textures, shapes, and human faces, each using features based on a different model of the image.

7.2 Surf-image system from INRIA, France [Nastar et al, 1998]. This, uses multiple types of image feature which can be combined in different ways, and offering sophisticated relevance feedback facilities.

7.3 Netra. The Netra system uses color texture, shape and spatial location information to provide region-based searching based on local image properties [Ma and Manjunath, 1997]. An interesting feature is its use of sophisticated image segmentation techniques.

7.4 Synapse. This system is an implementation of *retrieval by appearance* ble at (section 0) using whole image matching [Ravela and Manmatha, 1998b].

VIII. PRACTICAL APPLICATIONS OF CBIR

A wide range of possible applications for CBIR technology has been identified (e.g. Gudivada and Raghavan [1995a]). Potentially fruitful areas include:

Crime prevention

The military

Architectural and engineering design

Medical diagnosis

Education and training

Home entertainment

Web searching

:

8.1 Crime prevention

Law enforcement agencies typically maintain large archives of visual evidence, including past suspects' facial photographs (generally known as mugshots), fingerprints, tyre treads and shoeprints. Whenever a serious crime is committed, they can compare evidence from the scene of the crime for its similarity to records in their archives. Strictly speaking, this is an example of *identity* rather than *similarity* matching, though since all such images vary naturally over time, the distinction is of little practical significance. Face recognition is also a reasonably mature technology. Most current systems use either a version of the *eigenface* method initially developed for the Photobook system at MIT [Pentland et al, 1996], or local feature matching along lines proposed by Bach et al.

8.2 The military

Military applications of imaging technology are probably the best-developed, though least publicized. Recognition of enemy aircraft from radar screens, identification of targets from satellite photographs, and provision of guidance systems for cruise missiles are known examples – though these almost certainly represent only the tip of the iceberg. Many of the surveillance techniques used in crime prevention could also be relevant to the military field.

8.3 Architectural and engineering design

Architectural and engineering design share a number of common features – the use of stylized 2- and 3-D models to represent design objects, the need to visualize designs for the benefit of non-technical clients, and the need to work within externally-imposed constraints, often financial. Such constraints mean that the designer needs to be aware of previous designs, particularly if these can be adapted to the problem at hand. Hence the ability to search design archives for previous examples which are in some way similar, or meet specified suitability criteria, can be valuable.

8.4 Medical diagnosis

The increasing reliance of modern medicine on diagnostic techniques such as radiology, histopathology, and computerised tomography has resulted in an explosion in the number and importance of medical images now stored by most hospitals. While the prime requirement for medical imaging systems is to be able to display images relating to a named patient, there is increasing interest in the use of CBIR techniques to aid diagnosis by identifying similar past cases.

Most development work in the PACS (picture archiving and communication systems) area is still directed towards providing basic functionality (ensuring that medical images can be successfully digitized, stored and transmitted over local area networks without loss of quality) and usability (providing user-centred interfaces and integrating image storage and retrieval with wider aspects of patient record management). However, experimental content-based retrieval systems are beginning to have some impact. Examples of this include the I^2C system for retrieving 2-D radiological images from the University of Crete [Orphanoudakis et al, 1994], and the 3-D neurological image retrieval system currently being developed at Carnegie-Mellon University [Liu et al, 1998], both developed with the aim of assisting medical staff in diagnosing brain tumours.

8.5 Education and training

It is often difficult to identify good teaching material to illustrate key points in a lecture or self-study module. The availability of searchable collections of video clips providing examples of (say) avalanches for a lecture on mountain safety, or traffic congestion for a course on urban planning, could reduce preparation time and lead to improved teaching quality. In some cases (complex diagnostic and repair procedures) such videos might even replace a human tutor.

Reports of the application of CBIR technology to education and training have so far been sparse – though Carnegie-Mellon University's Informedia system is being trialled at a number of universities, including the Open University in the UK [van der Zwan et al, 1999]. It appears to be too early to form any definite conclusions about the system's effectiveness in practice.

8.6 Home entertainment

Much home entertainment is image or video-based, including holiday snapshots, home videos and scenes from favourite TV programmes or films. This is one of the few areas where a mass market for CBIR technology could develop. Possible applications could include management of family photo albums ('find that photo of Aunt Sue on the beach at Brighton') or clips from commercial films ('play me all the car chases from James Bond movies').

Despite a lack of published information about developments in this area, a number of large commercial organizations are known to be devoting substantial development effort into this problem at present, and are believed to be making significant progress. Despite some formidable difficulties – the software will need to offer effective semantic-level retrieval, be far easier to use than any of today's systems, and come at an affordable price – the rewards for success could be enormous. This application area has the potential to drive virtually all future CBIR development activity if it ever takes off.

8.7 Web searching

Cutting across many of the above application areas is the need for effective location of both text and images on the Web, which has developed over the last five years into an indispensable source of both information and entertainment. Text-based search engines have grown rapidly in usage as the Web has expanded; the well-publicized difficulty of locating images on the Web [Jain, 1995] indicates that there is a clear need for image search tools of similar power. Paradoxically, there is also a need for software to *prevent* access to images which are deemed pornographic.

IX. CONCLUSION

The extent to which CBIR technology is currently in routine use is clearly still very limited. In particular, CBIR technology has so far had little impact on the more general applications of image searching, such as journalism or home entertainment. Only in very specialist areas such as crime prevention has CBIR technology been adopted to any significant extent. This is no coincidence – while the problems of image retrieval in a general context have not yet been satisfactorily solved, the well-known artificial intelligence principle of exploiting natural constraints has been successfully adopted by system designers working within restricted domains where shape, color or texture features play an important part in retrieval research groups.

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