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Image Analysis Using Content Based Image Retrieval Technique

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ABSTRACT: Content Based Image Retrieval (CBIR) is a technology that effectively manages image understanding and machine learning. The conventional CBIR depends on difficult and prolonged methods to extract features from a general image. In this study, we focus on the use of texture data; description of image content to produce an advanced and effective geographic image retrieval system. This process is named as Content Based Geographic Image Retrieval (CBGIR) technique has been effectively used to retrieve applicable images on account of automatically derived features present in the geographical images, ever since researchers of remote sensing field have started to recognize the effectiveness of local feature-based analysis of high-resolution images. This paper illustrates the effective techniques and concepts related to it.

KEYWORDS: Content Based Image Retrieval, visual content, Multi-pass query, Integrated region matching, Quadratic distance

I. INTRODUCTION

Today more information the user can handle from business transactions and scientific data to satellite pictures, text reports and military intelligence. Image retrieval is simply not enough anymore for decision- making. One of the main problems was the difficulty of locating the desired image in a large and varied collection, while it is perfectly feasible to identify the desired image from a small collection simply by browsing. More effective techniques are needed with collections containing thousands of items.

Image and video storage and retrieval systems have typically relied on human supplied textual annotations to enable indexing and searches. The text-based indexes for large image and video archives are time consuming to create. They necessitate that each image and video scene is analyzed manually by a domain expert so the contents can be described textually. The language-based descriptions, however, can never capture the visual content sufficiently.

II. CONVENTIONAL TECHNIQUES

The problems with text-based access to images have prompted increasing interest in the development of image based solutions. This is more often referred to as Content Based Image Retrieval (CBIR). Content Based Image Retrieval relies on the characterization of primitive features such as colour, shape and texture that can be automatically extracted from the images themselves.

Queries to CBIR system are most often expressed as visual exemplars of the type of the image or image attributed being sought. For Example, user may submit a sketch, click on the texture pallet, or select a particular shape of interest. This system then identifies those stored images with a high degree of similarity to the requested feature.

Similar to classification, clustering is the organization of data in classes. However, unlike classification, clustering class labels are unknown and it is up to the clustering algorithm to discover acceptable classes[4].

III. CONTENT BASED RETRIEVAL

IBM's QBIC system is the first commercial CBIR system and probably the best known of all CBIR systems. QBIC supports users to retrieval images by colour, shape and texture. QBIC provides several query methods: Simple, Multi-feature and multi-pass. In the simple method, a query is processed using only one feature. A Multi-feature query involves more than one feature, and all features have equal weights during the search.

A Multi-pass query uses the output of a previous query as the basis for further refinements. Users can draw and specify colour and texture colour and texture patterns in desired images. In QBIC, the colour similarity is computed by quadratic metric using k-element colour histograms and the average colours are used as filters to improve query efficiency. Its shape function retrieves images by shape area, circularity, eccentricity and major axis orientation. Its texture function retrieves images by global coarseness, contrast and directionality features [3].

The Photo book system (developed at the Massachusetts institute of technology) allows retrieving images by colour, shape and texture features. This system provides a set of matching algorithms, including Euclidean, mahalanobis, divergence, vector space angle, histogram, Fourier peak, and wavelet tree distances as distance metrics. In its most recent version, users can define their own matching algorithms [5].

This system allows users to retrieve images by colour, texture and shape. Imatch supports several query similar images: Colour similarity, colour and shape (Quick), colour and Shape (Fuzzy), and colour distribution.

IV. SPATIAL IMAGE RETRIEVAL CONCEPTS

Currently the most widely used image search engine, the GOOGLE, provides its users with the textual annotation kind of implementation. With large volume of images added to the image database, not many images are annotated with proper description. So many relevant images go unmatched.

The most widely accepted content-based image retrieval techniques use the Quadratic Distance and the Integrated Region Matching methods. The Quadratic Distance method, though yields metric distance, is computationally expensive. The conventional Integrated Region Matching is non-metric and hence gives results that are not optimal. Our system uses a modified IRM method which overcomes the disadvantages of both the above-mentioned methods. The color feature is extracted using the commonly adopted histogram technique.

We also provide an interface where the user can give a query image as an input. The colour feature is automatically extracted from the query image and is compared to the images in the database retrieving the matching images.

A. Spatial data set concepts

A key distinction is that visual data exploration is a completely human guided process, whereas RM algorithms can automatically analyze a data set searching for useful information and statistically valid patterns. The degree of automation of RM algorithms actually varies considerably as different levels of human guidance and interaction are usually required, but still the algorithm, not the user, is the one that is to look for image patterns.

A spatial data set enhances the data by storing and analyzing the spatial component of operational data. This view dimension, location, gives decision makers more definition of their data and allows them to ask new questions about the relationship in their database. Online analytical processing the spatial data set extends the usefulness of Online Analytical Processing (OLAP) systems. OLAP systems are used by decision makers to interrogate the data set.

ESRI’s is the largest provider of spatial technology worldwide. This spatial technology known as a Geographic Information System (GIS), allows users to view, query and analyse their business data based on the locational context of their data. ESRI’s family of software products meets the need to spatially enable your data set. The user can create their own GIS configuration by selecting appropriate solutions from ESRI’s comprehensive family of products as your GIS requirements change or grow.

V. METHODOLOGY

Content-based image retrieval is one of the techniques for automatic retrieval of images from a database by colour, texture and shape features. The features used for retrieval can be either primitive or semantic but the abstraction process must be predominantly automatic.

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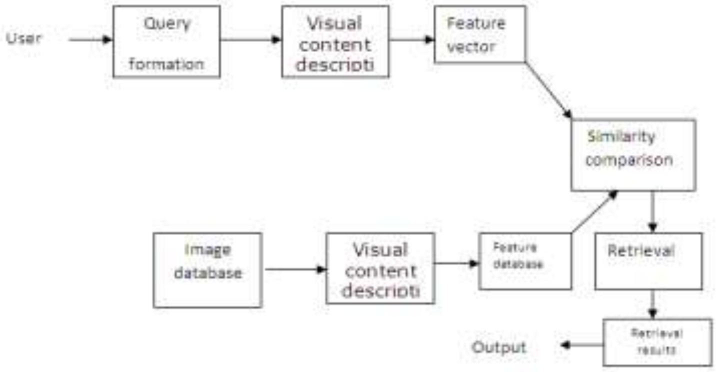


Fig 1. CONTENT BASED IMAGE RETRIEVAL SYSTEM

The goal of Content-Based Image Retrieval (CBIR) systems is to operate on collections of images and, in response to visual queries, extract relevant image. The application potential of CBIR for fast and effective image retrieval is enormous, expanding the use of computer technology to a management tool.

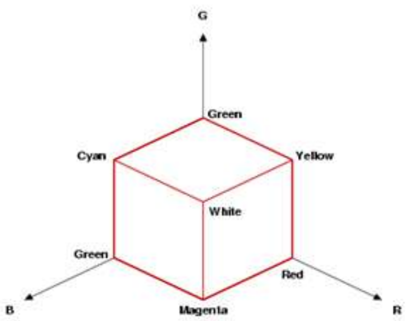
CBIR systems require methods that are based on the primitive features to compare the similarities or differences between an example image and all the images in the image collection. However, the similarities or differences between images cannot be qualified in an ideal manner. The extent to which the images are similar will change when query requirements are varied. For instance, in the case of two pictures, one of a blue sea with a sunrise and the other of a green mountain with a sunrise, when the sunrise is considered the similarity between the two images is low. We believe that it would be very difficult to find a method to measure the similarities or differences between images accurately for all kinds of query demands [1][2].

In other words, every retrieval method will have its own limits. For example, it will be hard for a colour based image retrieval technology to differentiate an image of blue sky from an image of blue sea. Therefore, when evaluating a CBIR technology, oneshould remember that the retrieval effectiveness of that technology depends on the types of query requirements that users make.

A. Histogram Similarity Distance approach

The human eye is sensitive to colors, and color features are one of the most important elements enabling humans to recognize images. Color features are, therefore, fundamental characteristics of the content of images. Color features can most often provide powerful information for categorizing images, and they are very useful for image retrieval. Therefore, color based image is widely used in CBIR systems[6][7].

Color histograms are generally used to represent the color features of images. Before using color histograms, however, we need to select and quantify a color space model and choose a distance metric



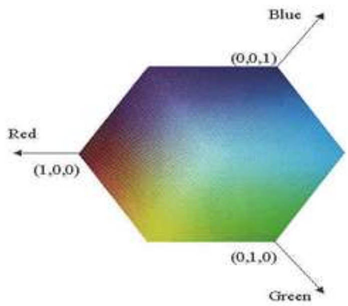


Fig2 a. RGB COORDINATES SYSTEM Fig 2.b.**RGB COLOR MODEL**

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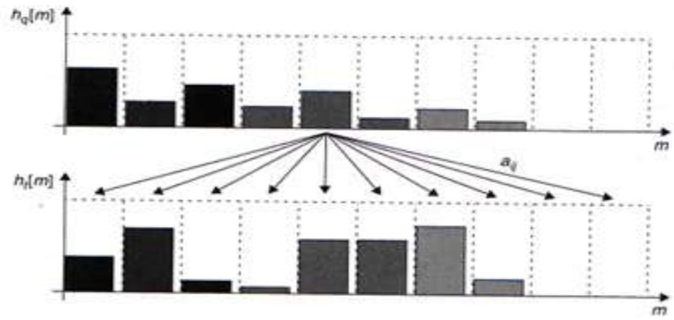
Histograms can also be taken of color images, either individual histograms of red, green and blue channels can be taken, or a 3-D histogram can be produced, with the three axes representing the red, blue and green channels, represented by figure 2.a and figure 2.b, and brightness at each point representing the pixel count. The exact output from the operation depends upon the implementation.

B. Histogram Quadratic Distance measures

To address the shortcomings of Min kowski-form metrics in comparing only "like" bins, quadratic-form metrics consider the cross-relation of the bins. As shown in Figure 3, the quadratic-form metrics compare all bins and weight the inter-element distance by pair wise weighting factors.

Histogram Quadratic distance measures (d4)

The IBM QBIC system developed a quadratic-form metric for color histogram-based image retrieval, reports that the quadratic-form metric between color histograms provides more desirable results than "like-color"-only comparisons. The quadratic-form distance between color histograms hq and ht.



$$\mathcal{D}4(\mathbf{q},\mathbf{t}) = D4^2 = (\mathbf{h}_q - \mathbf{h}_t)^T \mathbf{A} (\mathbf{h}_q - \mathbf{h}_t),$$

Fig3. Histogram Quadratic Distance measures

Quadratic-form metrics compare multiple bins between the color histogram using a similarity matrix A = [aij], which can take into account color similarity or color Covariance[8][9].

VI. COMPARISON OF HISTOGRAMS OF IMAGES

One important aspect of any CBIR system is the distance used to compare the visual features extracted from the images. The better the distance simulates the human perception of similarity using the available visual features, the more effective is the CBIR system in retrieving relevant images to the user's need. The computational complexity of the distance is another important issue when processing a visual query. Depending on the distance complexity, the time to compute the distance between images must be superior to the time to access the disk pages where the visual features are stored.Let h and g represent two color histograms. The Euclidean distance between the color histograms h and g can be computed as:

$$d^2(h,g) = \sum_A \sum_B \sum_C (h(a,b,c) - g(a,b,c))^2$$

In this distance formula, there is only comparison between the identical bins in the respective histograms. Two different bins may represent perceptually similar colors but are not compared cross-wise. All bins contribute equally to the distance[10][11].

Regional CBIR approaches are better modeled in a metric space. A metric space is composed by a set of elements (in our case, these elements are visual features) and a metric distance to compare these elements. In metric spaces, there are no restrictions about the representation of visual features. In this case, what really matter are the metric properties of the distance used to compare the visual features. A distance d is considered a metric if, for any (images) X, Y and Z, the following properties hold:

Positiveness or Minimality: d(X, Y) >= 0
Symmetry: d(X, Y) = d(Y, X)
Reflexivity or Self-similarity: d(X, X) = 0

Triangular Inequality:
d(X, Z) <= d(X, Y) + d(Y,Z)
Metric spaces can be efficiently indexed using metric access methods (MAMs). These methods make extensive use of triangular inequality

property to reduce the search space and also the number of distance computations at query time[7].

VII. CONCLUSION

Content based Image Retrieval (CBIR) system aims at retrieval of images of relevance to the query image input by the user from an enormous image database by low-level feature (such as color, texture and shape) extraction from the image. CBIR has proved to be of great help in applications such as Face recognition, Medical diagnosis, prevention of Crime, Geospatial Satellite Imaging and several other applications that require a fast and efficient retrieval system for relevant image extraction from enormous image databases. Conventional color histogram, Color Moments, Color Auto Correlogram, Dominant Color Descriptor are the color feature extraction techniques. CBIR still faces some challenges like judgment of human perception of visual content, less appropriate selection of similarity measure, semantic gap and other factors.

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