Geo Spatial Image Retrieval Using Content-Based Image Retrieval Technique

B Sunil Kumar, P.Neelakantan, J.Velmurugan and B Lakshmana Rao

***Abstract*---Searching for relevant knowledge across heterogeneous geospatial databases requires an extensive knowledge of the semantic meaning of images, a keen eye for visual patterns, and efficient strategies for collecting and analyzing data with minimal human intervention. In this paper, we present our recently developed content-based Geospatial Image Retrieval includes Content-based image retrieval Technique (CBIR). CBIR use the Quadratic Distance and the Integrated Region Matching (IRM) methods. The Quadratic Distance method, though yields metric distance, is computationally expensive.**

The IRM novel similarity measure for region-based image similarity comparison that gives optimal solution. The targeted image retrieval systems represent an image by a set of regions, roughly corresponding to objects, which are characterized by features reciting colour, texture, shape, and location properties. The IRM measure for evaluating overall similarity between images incorporates properties of all the regions in the images by a region-matching scheme. Compared with retrieval based on individual regions, the overall similarity approach reduces the innocence of inaccurate segmentation, helps to clarify the semantics of a particular region, and enables a simple querying interface for region-based image retrieval systems and after finding some feasible set of images using IRM, this system considers one of the image from the set as input and determines unique image as optimal solution.. Our system in general achieves more accurate retrieval at higher speed.

INTRODUCTION

Every day the average person with a computer faces a growing flow of multimedia information particularly via the Internet. But this ocean of information would be useless without the ability to manipulate, classify, archive and access them quickly and selectively. While text indexing is ubiquitous, it is often limited, tedious and subjective for describing image content.

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.

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II. CONVENTIONAL TECHNIQUES

To date, 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-base descriptions, however, can never capture the visual content sufficiently.

For example, a description of the overall semantic content of an image does not include an enumeration of all the objects and their characteristics, which may be of interest later. A content mismatch occurs when the information that the domain expert ascertains from an image differs from the information that the user is interested in. A content mismatch is catastrophic in the sense that little can be done to approximate or recover the omitted annotations. In addition, a language mismatch can occur when the user and the domain expert use different languages or phrases. Because text-based matching provides only hit-or-miss type searching, when the user does not specify the right keywords the desired images are unreachable without examining the entire collection.

III. CONTENT BASED RETRIEVAL

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 color, 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.

IV. OUR SYSTEM

Currently the most widely used image search engine, the GOOGLE, provides its users with the textual annotation kind of implementation. With lacks 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 color feature is automatically extracted from the query image and is compared to the images in the database retrieving the matching images

V. CLASSIFICATION OF CBIR SYSTEMS

Existing CBIR systems based on low-level visual features can be classified into three main categories. They are:

1. Global approaches
2. Partition-based approaches
3. Regional approaches
4.

A. Global approaches

Global approaches describe the visual content of an image as whole without spatial or topological information. Several features have been used to represent images in CBIR systems. The most commonly used feature is colour. Global colour histogram is an example for this. It is simple and effective way of utilizing the colour features. The GCH is an n-dimensional vector C = {c(1),c(2),……..c(n)) where each element C_J represents the percentage of pixels of colours J in an image

B. Partition based approaches

Partition based approaches introduce some spatial information about the visual content of images, decomposing them in spatial cells, according to a fixed scheme and describing the content of each cell individually An example for this is the local color histograms. An image is portioned into equal sized sub images/blocks and the similarity between two images is based on the histogram distances between corresponding blocks

C. Disadvantages

1. It is not capable of handling geometric transformations like rotation and translation.
2. Problems like variance to absolute spatial location.

Regional approaches in the sense that instead of decomposing images in a fixed way, these approaches exploit their visual content to achieve a more flexible and robust segmentation. Unlike partition cells, segmented regions of two distinct images may have different size, position and shape. Moreover the number of two images may be different.

VI. CURRENT CBIR APPROACHES

CBIR operates on the principle of retrieving stored images from a collection by comparing features automatically extracted from the images themselves. The commonest features used are mathematical measures of colour, texture or shape. A typical system allows users to formulate queries by submitting an example of the type of image being sought, though some offer alternatives such as selection from a palette or sketch input. The system then identifies those stored images whose feature values match those of the query most closely, and displays thumbnails of these images on the screen

A. Regional approaches

Domain specific features: -Fingerprints, Human faces

Visual features

General features: - Colour, texture, shape some of the most commonly used types of features

used for image retrieval are as follows

B. Colour retrieval

Several methods for retrieving images on the basis of colour similarity have been described in the literature, but most are variations on the same basic idea. Each image added to the collection is analysed to compute a colour histogram, which shows the proportion of pixels of each colour within the image. The colour histogram for each image is then stores in then stored in the database. At each time, the user can either specify the desired proportion of each colour (&75% olive green and 25% red, for example), or submit an example image from which a colour histogram is calculated. Either way, the matching process then retrieves those, which a colour histogram is calculated. Either way, the matching process then retrieves those images whose colour histograms match those of the query most closely.

C. Texture retrieval

The ability to match on texture similarity can often be useful in distinguishing between areas of images with similar colour (such as blue sky and sea or green leaves and grass). A variety of techniques has been used for measuring texture similarity; the best established rely on comparing values of what are known as second-order statistics calculated from query and stored images. Essentially, these calculate the relative brightness of selected pairs of pixels from each image. From these it is possible to calculate measures of image texture such as the degree of contrast, coarseness, directionality and regularity or periodically, directionality and randomness.

Texture queries can be formulated in a similar manner to colour queries, by selecting examples of desires texture a palette, or by supplying an example query image. The system then retrieves images with texture measures most similar in value to the query.

D. Shape retrieval

Two major steps are involves in shape feature extraction. They are object segmentation and shape representation.

Object segmentation: Segmentation is very important to Image Retrieval. Both the shape feature and the layout feature depend on good segmentation allow fast and efficient searching for information of a user's need.

Shape representation: In image retrieval, depending on the applications, some requires the shape representation to be invariant to translation, rotation, and scaling. In general, the shape representations can be divided into two categories, **boundary-based** and **region-based**. The former uses only the outer boundary of the shape while the latter uses the entire shape region

VII. 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. Such a distance affects directly the time spent to processing a visual query and the quality of the retrieval (effectiveness). 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.

Unfortunately, regional CBIR approaches cannot be adequately modeled in a vectorial space, because the number of regions of two images may be different and the obtained regions may also have different sizes. As a consequence, the comparison of images is usually based on complex distance functions.

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)

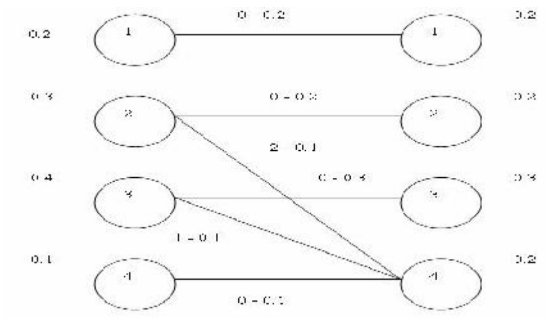
Metric spaces can be efficiently indexed using metric access methods (MAMs). These methods make extensive use of triangular inequality property to reduce the search space and also the number of distance computations at query time.

The main problem to model a regional CBIR approach in metric space is related to the distance used to compare segmented images.

A. True IRM

The distance irm(X,Y) between two images X and Y is algorithmically described below, and works as follows. Initially, all distances dhist(Xi, Yj) between the pairs of levels are computed , checked for the monge condition,and ordered. Additionally, all levels are initialized as "non-matched" (status = 0). The distance dhist(Xi, Yj) depends on the visual features extracted from the levels. In our case it is weighted composition of the distance between the histogram levels and the distance between the sizes of the levels (bins).

After ordering the distances, the first value corresponds to the best possible match between a level of image X and a level of image Y. The second value corresponds to the second best match and so on. For each distance dhist(Xi, Yj) in a non-decreasing order, if both levels are marked as non-matched,and check the monge condition, the size of levels Xi and Xj are compared. The size of the smallest level determines the weight w that multiplies the values dhist(Xi, Yj) in order to obtain the final distance between the images ( ). This weight represents to percentage of matching between the two images with that distance.



In each iteration of the for loop, the smallest level is marked as "matched" (status =1). This means that the full content of the level was matched. Thus, any other distance related to this level in the next iterations should be discarded. Since at each iteration, the largest region may not be completely matched, we subtract the size of the smallest level (the percentage of level actually matched) from the size of the largest one. After this operation, if the size of the level equals zero (occurs when the two compared levels have the same size), both levels are marked as matched. If the size of the largest level remains greater than zero, then we continue analyzing distances involving this level until its size equals zero. Observe that, at the end of the process, the sum of the weighted values w equals 1, meaning that the entire image content was compared.

B. Monge condition:

Hoffman proved that, if distance matrix satisfies the monge condition,then greedy approach gives optimal solution.

$$a_{ij} + a_{kl} \leqslant a_{il} + a_{kj} \quad \text{for any } i < k, \ \ j < l$$

Our histogram distance matrix implicitly satisfies the monge condition. Hence our approach gives optimal solution that is metric distance. So we called our modified IRM, **Geo Spatial Image Retrieval using IRM.**

This system computes histograms of every image in the database and takes one input image to search from the database. It gives feasible solution consisting finite number of images *(Say 'X')* having minimum IRM distance. Then by taking minimum IRM distance image *(Say 'x', where x X)* as input and remaining images in the feasible solution set as a database of images applies region matching technique. Hence, it computes single image having minimum IRM distance with **'x'**.

CONCLUSION

In this work we experimented with the idea of ***Geo Spatial for image retrieval*** *using Integrated Region Matching* to histograms for similarity measure based on their color content. A measure of the over-all similarity between images, defined by our approach, incorporates all local properties of the histograms of the images. We proved that our True IRM approach gives metric distance and hence better results compared to existing histogram methods.

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