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Content Based Image Retrieval of Satellite Imageries Using Soft Query Based Color Composite Techniques

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ABSTRACT

There has been a focus on developing image indexing techniques which have the capability to retrieve image based on their contents. The technologies are now generally referred to as Content-Based Image Retrieval (CBIR). Due to its extensive potential applications, CBIR has attracted a great amount of attention in recent years. Using colors as the content, content based image processing have been carried out for a sample of high resolution urban image and low resolution rural image scenes obtained from satellites. The color based processing has been utilized to identity important urban features such as buildings and gardens and rural features such as natural vegetation, water bodies and fields applying various techniques. The techniques included color based extractions using neighborhood rules and histograms. An estimation of the features and available resources from the imageries have been made using the color spectral graphs. The results of the analysis are presented and discussed in the paper.

Keywords

Feature Extraction, histogram, spectral graph, Distance measurement, Neighborhood search, Soft query, Content generation, Pixel distribution, high resolution and low resolution image.

Introduction

Recent years have witnessed the rapid increase of digital images around the world, due to the growing power of workstations, decreasing storage and processing costs and the Internet. However, instead of making things easier, the sheer huge amount of digital images stored around the world makes the utilization of images from existing database more difficult than ever. This is due to the lack of a standard way of indexing and managing digital images. The advantage of textual indexing of image is that it can provide user with key word searching, catalogue browsing and even with query interface such as Structural Query Language (SQL). However, it apparently has limitations. One is that it is time consuming, when the database is large, it is almost impossible to manually annotate all the images. The other is visual features of image are difficult to be described using words.

In CBIR, images in the databases are unstructured data; digitized images consist purely of arrays of pixel intensities, with no inherent meaning. One of the key issues with CBIR is the need to extract useful information from the raw data to reflect the image content. As such, the extraction of effective content features is crucial to the success of CBIR. Studies on users' requirements for image from image collections reveal that primitive features such as color, texture, shape or the combination of them are very useful for image description and retrieval. These features are both objective and directly derivable from the images themselves, without the need to refer to any external knowledge base. Therefore, primitive low level image features can be derived and exploited to support automatic CBIR.

Digital images databases however, open the way to content-based searching. In this paper we survey some technical aspects of current content-based image retrieval systems. The purpose of this survey however, is to provide an overview of the functionality of temporary image retrieval systems in terms of technical aspects: querying, relevance feedback, features, matching measures, indexing data structures, and result presentation. It compares specific systems, rather than general architectures, and provides a basis for (or defense against) statements like "this or that system already does what your system does". It also is a thorough foundation for claims that most systems use low level features, and few use high level semantic meaningful features.

Search strategies

Content-based retrieval of image and video databases usually involves comparing a query object with the objects stored in the data repository. The search is usually based on similarity rather than on exact match, and the retrieved results are then ranked according to a similarity index. Objects can be extracted from an image at ingestion time, composed at query time, or retrieved using a combination of the above strategies. In most cases, compromises have to be made between generality and efficiency. Objects extracted at image ingestion time can be indexed much more efficiently. However, it is usually very difficult to anticipate all the types of objects in which a user might be, and thus systems allowing only search based on pre-extracted objects are severely limiting. On the other hand, recognizing objects entirely at query time will limit the scalability of a system, due to the high expense of such computing.

To alleviate both problems, we propose a object-oriented framework which allows flexible composition of queries relying on both types of objects. Within this framework, objects can be specified at multiple abstraction levels

Raw Data

At the lowest abstraction level, objects are simply aggregations of raw pixels from the image. Comparison between objects or regions is done pixel-by-pixel. Commonly used similarity measures include the correlation coefficient and the Euclidean distance. Comparison at the pixel level is very specific, and is therefore only used when a relatively precise match is required.

Feature

The next higher abstraction level for representing images is the feature level. An image feature is a distinguishing primitive characteristics or attribute of an image. Some features such as luminance, shape descriptor, and gray scale texture are natural since they correspond to visual appearance of an image. Other features such as amplitude histogram, color histogram, and spatial frequency spectra lack a natural correspondence. Different features are often grouped into feature vectors. Images in an archive can be segmented into regions characterized by homogeneous feature vectors. Similarity search in the n-dimensional feature space thus consists of comparing the target feature vector with the feature vectors stored in the database. An object-oriented definition of a feature object involves prescribing a set of pertinent features as well as a method (such as a clustering algorithm with the appropriate parameters) which characterizes the homogeneity of the object. Feature objects can be predefined and pre-extracted, user-defined and constructed at query time using pre-extracted features, or even user-defined and extracted at query time. Various spatial indexing schemes such as R-Trees can be used to facilitate feature space indexing.

Semantic

This is the highest abstraction level at which a content-based search can be performed. An object-oriented definition of a semantic object also involves prescribing a set of pertinent features or pixels as well as a method (such as a classification algorithm with the appropriate training data). For satellite images, examples of semantic objects include the type of land cover for a specific area such as water, forest, or urban. A semantic network can be constructed which groups similar semantic terms into a categories. For example, pine and maple are grouped into trees, rose and sunflower are grouped into flowers, corn and wheat are grouped into crops, etc. The purpose of constructing such a semantic network is to allow the generalization of retrieval at the. The purpose of constructing such a semantic network is to allow the generalization of retrieval at the semantic level.

Defining a Distance Measure on Images

An important component of the model for image analysis is a distance between images. A digital image $X = \{X_{ij} \mid i = 1, \ldots, n_1;\ j = 1, \ldots, n_2\}$ is a matrix of pixels, each pixel having one color X_{ij}. Color is defined by a vector of 3 values $X_{ij} = (X_{ij1}, X_{ij2}, X_{ij3})$, typically defining the red, green and blue components of the pixel color, although there are many other parameterisations that are possible and useful.

An image feature is defined to be any real-valued function of X. Many statistical features mean, variance, autocorrelations, and histograms can be defined. Letting $f(X) \in R^d$ be a vector of d features of the image X, then we can define the distance between two images X_1 and X_2 to be the distance in Rd between their feature vectors:

$$d(X_1,X_2) = \|f(X_1) - f(X_2)\|;$$

Euclidean or a Mahalanobis distance are usually chosen. The intention is that images that are close "semantically" are also close in feature space. Of course this can never be true for all circumstances and all interpretations of a image, a fact that is known as the semantic gap.

In what follows we use a set of some 600 features for each image: summary statistics such as means and variances, color histograms, autocorrelations between neighboring pixels, color coherence vectors (a measure of how large are areas of similar colors) and the location and size of objects in the image, obtained from a segmentation algorithm.

These are divided into 3 groups:

- Global color features (such as summary statistics of the entire image and histograms)
- Texture features (such as autocorrelations).
- And segmentation features.

For each group, a principal components analysis was conducted, reducing the dimension of the feature space to about 100, which were then normalized to lie in (0, 1).

Soft Query Behavior

The soft query results are obtained by incorporating user perceptions into the query processing. Therefore, the system needs a special mechanism for integrating image information and user perceptions into the query processing.

Query Processing Model

Each query statement can be decomposed into several atomic clauses. Some clauses access and process feature-values, and the others utilize property classes. Therefore, our soft query model consists of two different query processing methods: feature query and property query. These two query models compute the image membership separately and combine their results at the final step. The final query results are ordered according to their membership values. The feature query model is straightforward and simply involves the Boolean evaluation of the predicates.

Property Queries

A sample property query is: "Find all images with the classic style." The results of this type of queries depend on the user submitting the queries. The probability of an image belonging to the result set is presented by a real number between 0 and 1. The challenge is how to take all the information about the trusted evaluators and their classifications into account when processing a query.

The membership $\lambda_{d,c}$ of image d to a property class c given by user u can be computed using various aggregation functions. However, the aggregation functions with a triangular norm are preferred with our system. These aggregation functions g satisfy the properties - Conservation, Monotonic, Commutatively and Associatively. With these properties, the query optimizer can replace the original query with a logically equivalent one and still obtain the exactly same result.

Combination of Feature and Property Queries

The proposed query processing model for soft query can capture user queries on both features and properties in a unified manner. To compare our model with the conventional image retrieval systems, consider a typical "query by example" on color, shape, and texture of images. Conventional systems compute a weighted average over these perceptual features to measure the similarity distance between two images. The weights are assigned and fine-tuned either directly by the user or by the system after several iterations of monitoring the users' feedbacks. For example, the system will assign higher weights to the color feature for a color-oriented user. These perceptual features can also be modeled within our system as different properties. Subsequently, their weights are assigned not only by the user and his/her previous feedbacks but also by the other users/evaluators trusted by this user. In addition, our model can employ various feature extraction algorithms, semantic classes and soft memberships. For objects in the same category, and very different for object in the different category. This lead to idea of seeking distinguishing feature that is invariant to irrelevant transformation of the input.

The task of the classifier component of a full system is to use the feature vector provided by feature extraction to assign object to the category. The degree of difficulty of the classification problem defends on the variability in the feature values for the object in the same category relative to the difference between feature values in the different categories. The variability of feature values in the same category may be due to complexity and may be due to noise. Noise in defined in very general terms: any property in sensed pattern which is not due to an underlying model but instead to randomness in the word or the sensors.

Results and Discussions

Table 1: Image Data Format

Image type	Size	Bytes	Class
High resolution image-fig1(a)	768×1024×3	2359296	8
Low resolution Image- fig1(b)	571×995×3	1704435	8

Two samples of satellite images have been selected for a high resolution urban scene of a college campus shown in Fig 1(a) and a Rural image scene shown in Fig 1 (b). The data formats for the two images are given in table 1. It is evident from the figures that the features in the Urban Image are more clearly distinguishable than the features seen in the Rural Image.

Figure 1(a)- High Resolution satellite image

Figure 1(b)- Low Resolution satellite image

For the two selected satellite imageries, we have derived histograms for both urban scene and rural scene. Fig 2(a) and 2(b) shows the histograms for the two images. The figures in both cases show only single peak and indicate histogram techniques are not adequate to distinguish the features in the satellite images.

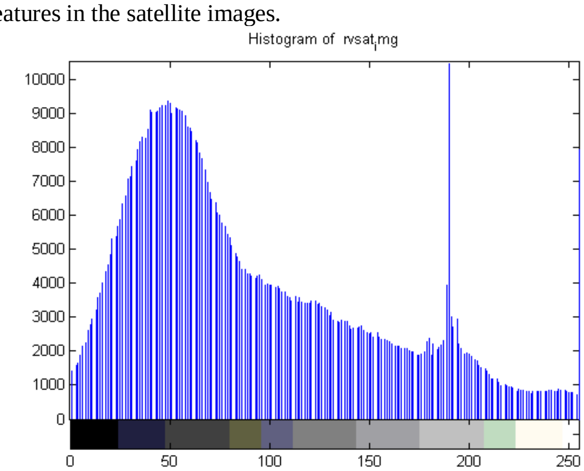


Figure 2(a)-Histogram of figure 1(a)

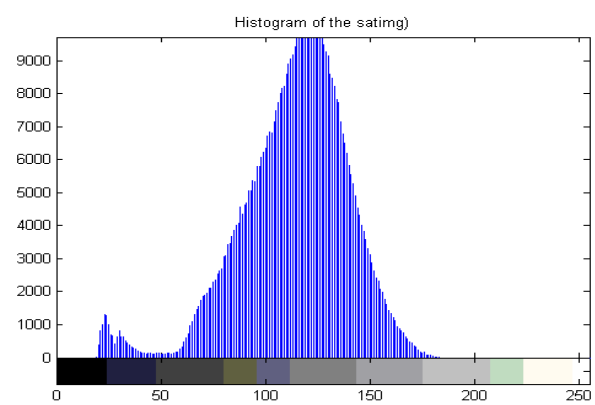


Figure 2(b)-Histogram of figure 1(b)

In order to identify the features contained in the Urban and Rural satellite images, the spectral graph of the images in L *a*b* composite colors have been plotted. The fig 3(a) & 3(b) shows the composite color distributions for the urban and rural images. The L*a*b* color composite values derived for the two images are displayed in table2. It is clearly seen from the figure 3(a), that the high resolution urban image exhibits a wide color distribution indicating the presence of the many distinguishable features in the image. Where as figure 3(b) shows that for a rural image the composite color distribution is highly concentrated on two or three features. Hence for Rural images it is not possible to resolve the colors and hence the features from the composite color distribution.

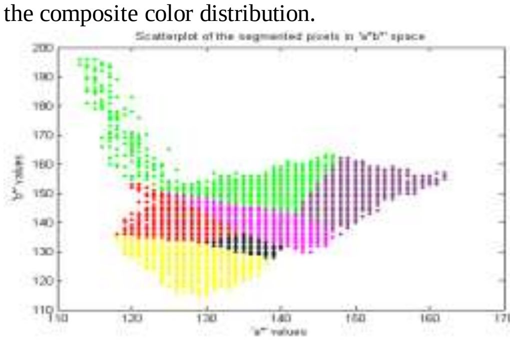
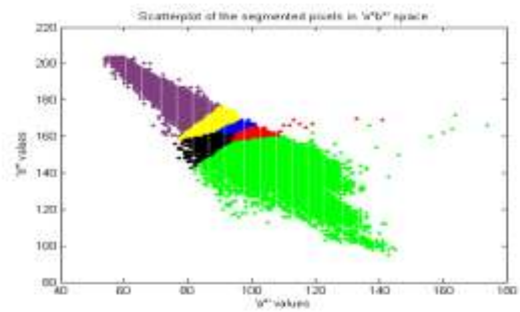


Figure 3(a)-Spectral graph of figure1(a)Figure



3 (b)- Spectral graph of figure1(b)

Table2 : Color composite table

Images	Pixel distribution ratio in terms of a* & b* composite colors	
Low resolution image(RV image)	*131.071,*	*134.825*
High resolution image(satellite image)	*81.968*	*173.548*
Satellite image sample1	*83.381*	*171.595*
Satellite image sample2	*94.833*	*157.365*

Feature Extraction in High resolution satellite urban image

The conceptual boundary between feature extraction and classification proper is some what arbitrary: An ideal feature extraction would yield as to representation that makes a job of classifier trivial. Conversely an omnipotent classifier would not need the help of a sophisticated feature

extractor. The traditional goal of feature extractor is to characterize an object to be recognized by measurements whose values are very similar
pixel most closely matches that color marker.

The features seen in the high resolution Urban image fig 1(a) can be separated by using color segmentation technique and Matlab simulation. The four important features that can be extracted using color based content image processing is shown in fig 4(a), 4(b), 4(c) & 4(d). The features corresponding to the distribution of buildings are evident in fig 4(d). The features representing the Green vegetation present in the gardens are clearly visible in fig 4(b). The fig 4(a), shows the land (soil) distribution in the image . Fig 4(c) gives the combination of green vegetation and soil distribution in the image scene. The figures clearly demonstrate the distribution of three important features such as soil, buildings, green vegetation present in the urban scene.

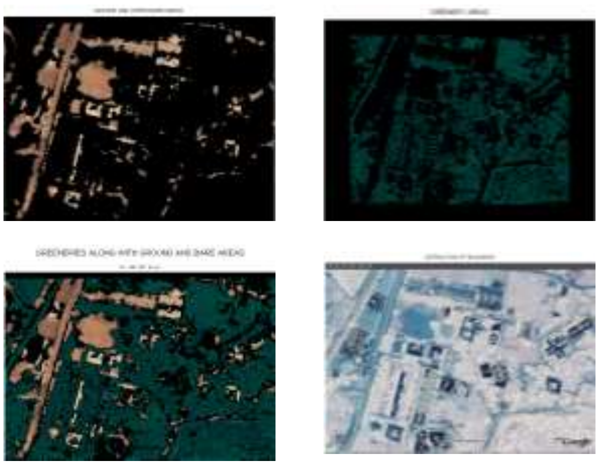


Figure 4(a)-Ground region extraction
Figure 4(b)-Green region extraction
Figure 4(c)-Ground and green region extraction
Figure 4(d)-Buildings extraction

Feature Extraction in Low resolution satellite rural image

The rural image has been divided into four parts and the two parts which contains the maximum number of features are selected for further analysis. Each pixel is classified based on Nearest Neighbor Rule. Further each pixel in the lab fabric image is classified by calculating the Euclidean distance between that pixel and each color marker. The smallest distance will tell us
that the pixel most closely matches that color marker. The label matrix contains a color label for each pixel in the satellite image. Label matrix has been used to separate objects in original image by color. This nearest neighbor classification is done by using fuzzy c-means standard equation. Bello figures shows green part separated images with black color as non greenery regions. Some parts of the retrieved images are highly green and some are lighter it showing how the distribution of colors varies in the given image.

The features extracted based on color content classification for the two selected potions of rural images are shown in the figure 5(a_1) and 5(a_2). The features extracted based on green color (Vegetation) classification are shown in figure 5(b_1) and 5(b_2). The features extracted based on classification of water bodies are shown in figure 5(c_1) and 5(c_2). It is evident from the figure that only two major features, the vegetation and water bodies can be extracted from the color based content techniques. The evidence presented in the figure suggest that for a low resolution rural image only dominant features such as green vegetation and water bodies can be extracted .

Figure5(a1)& 5(a2)- Division sample of figure1(b)

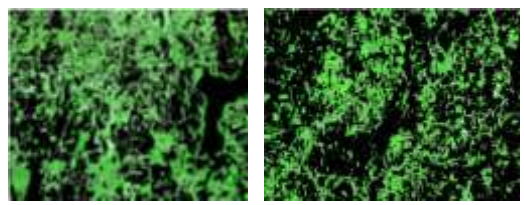


Figure 5(b1)& 5(b2)- Greenery extraction Figure 5(a)

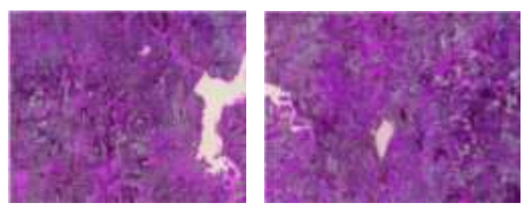


Figure 5(c1) & 5(C2)-Water body extraction Figure 5(a)

Image histograms are intensity transformers and it increases the contrast level of the image by performing histogram equalization. Histogram plot of an image is useful in analysis of a given image. We can obtain histogram plots by using function called "imhist".

In order to identify other features present in the rural image the histogram techniques described above are used. Figure 5(d_1) and 5(d_2). Shows the histograms for two images. The figure clearly illustrate the presence of four peaks in both the histograms indicating the presence of at least four features in the Rural images which is not apparent in the from the color based classification of the images.

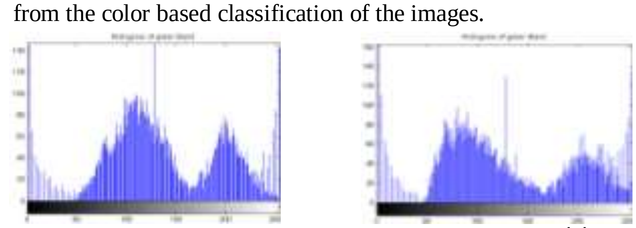


Figure 5(d1)&5(d2)- Histogram of figure5(a)

Conclusions:

The results and discussions presented for drawing the following conclusions

1. The various features present in a high resolution satellite urban imageries can be easily extracted from color based content processing and classification

2. The features identified in the urban image include Buildings, Gardens, and open Land

3. The features present in the rural images cannot be easily extracted from color based content processing techniques.

4. The histogram techniques are found more suitable for identification of the various features present in a satellite rural image.

5. The major features identified in a rural image includes, Vegetation, Water bodies in a rural scene.

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