Retrieval of Remote Sensing Images based on Color Moment and GLCM

Naveen Kumar Boddukuri[1] and Santosh Kumar Bairappaka[2]

[1] Deparment of Electronics & Communication, Christu Jyothi Institute of Technology
Warangal, Andhra Pradesh, India
[2] Deparment of Electronics & Communication, Christu Jyothi Institute of Technology
Warangal, Andhra Pradesh, India

Abstract: The remote sensing image archive is increasing day by day. The storage, organization and retrieval of these images poses a challenge to the scienitific community. In this paper we have developed a system for retrieval of remote sensing images on the basis of color moment and gray level co-occurrence matrix feature extractor. The results obtained through prototype system is encouraging.

Keywords: Remote Sensing Image Retrieval, Color Moment, Gray Level Co-occurrence Matrix, Clustering index.

I. Introduction

Content-based image retrieval (CBIR) technology was proposed in 1990s and it is an image retrieval technology using image vision contents such as color, texture, shape, spatial relationship, not using image notation to search images. It resolves some traditional image retrieval problems, for example, manual notations for images bring users a large amount of workload and inaccurate subjective description. After more than one decade, it has been developed as content-based vision information retrieval technology including image information and video information. Great progress has been made in theory and applications.

At present, CBIR technology obtains successful applications in face reorganization fields, fingerprint reorganization fields, medical image database fields, trademark registration fields, etc., such as QBIC system of IBM Corporation, Photobook system of MIT Media Laboratory and Virage system of Virage Corporation. It is difficult to apply these systems in massive remote sensing image archive because remote sensing image has many features including various data types, a mass of data, different resolution scales and different data sources, which restrict the application of CBIR technology in remote sensing image field. In order to change the current situation, we must resolve some problems as follows.

1. Storing massive remote sensing image data.
2. Designing reasonable physical and logical pattern of remote sensing image database.
3. Adopting adaptive image feature extraction algorithms.
4. Adopting indexing structure for search.
5. Designing reasonable content based searching system of massive remote sensing image database.

The rest of the paper is arranged as follows. In Sec. 2, we discuss the methodology. In Sec. 3, the experimental setup and the results obtained are discussed. We conclude in Sec. 4.

II. Methodology

For practical applications, users are often interested in the partial region or targets, such as military target, public targets and ground resource targets in remote sensing image instead of the entire image. For example, the small scale important targets and regions of remote sensing image arrest more attention than the entire remote sensing image in application. These image slice features of important targets and regions extracted by color, texture, shape, spatial relationship, etc. are stored in feature database. Efficient indexing technology is a key factor for applying the content-based image retrieval in massive image database successfully. Indexing technology developed from traditional database and has been applied in content-based image retrieval field subsequently. Fig.1 shows an architecture frame of content-based remote sensing image.

Traditionally, satellite image classification has been done at the pixel level. For a typical LISS III image has 23.5m resolution, a 100 × 100 sized image patch covers roughly 7.2 Km^2. This is too large an area to represent precise ground segmentation, but our focus is more on building a querying and browsing system than showing exact boundaries between classes. Dividing the image into rectangular patches makes it very convenient for training as well as browsing. Since users of such systems are generally more interested in getting an overview of the location, zooming and panning is allowed optionally as part of the interface.

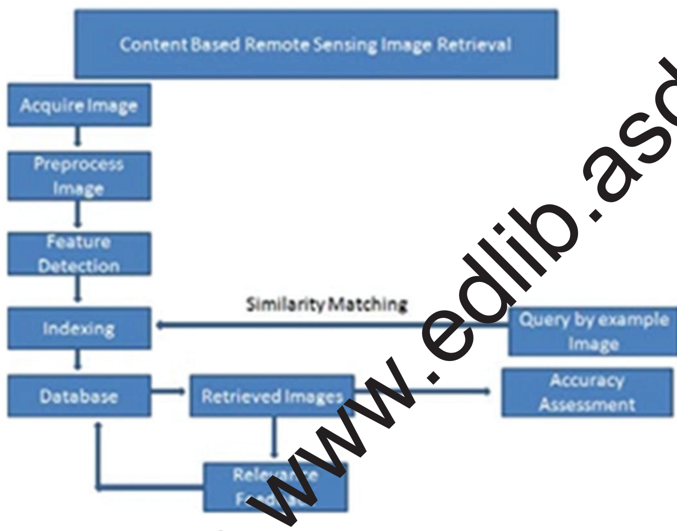

Figure 1: Architectural Framework of CBIR system

We have developed a prototype system for image retrieval. In this a query image is taken and images similar to the query images are found on the basis of color and texture similarity. The three main tasks of the system are:

1. Color Moment Feature Extraction
2. GLCM Texture Feature Extraction.
3. K-means clustering to form index.
4. Retrieval between the query image and database.

2.1 Color Moment

We will define the i^{th} color channel at the j^{th} image pixel as p_{ij}. The three color moments can then be defined as:

Moment 1 - Mean:

$$E_i=\sum_{N}^{j=1}\frac{1}{N}p_{ij}$$

Mean can be understood as the average color value in the image.

Moment 2 -Standard Deviation:

$$\sigma_i = \sqrt{\left(\frac{1}{N}\sum_{N}^{j=1}(p_{ij} - E_i)^2\right)}$$

The standard deviation is the square root of the variance of the distribution.

Moment 3 - Skewness:

$$s_i = \sqrt[3]{\left(\frac{1}{N}\sum_{N}^{j=1}(p_{ij} - E_i)^3\right)}$$

Skewness can be understood as a measure of the degree of asymmetry in the distribution.

2.2 Grey-Level Co-Occurrence Matrix Texture

Grey-Level Co-occurrence Matrix texture measurements have been the workhorse of image texture since they were proposed by Haralick in the 1970s. To many image analysts, they are a button you push in the software that yields a band whose use improves classification - or not. The original works are necessarily condensed and mathematical, making the process difficult to understand for the student or front-line image analyst.

Calculate the selected Feature. This calculation uses only the values in the GLCM. See:

i. Contrast
ii. Correlation
iii. Energy
iv. Homogeneity

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2$$

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij}\frac{(i-\mu)(j-\mu)}{\sigma^2}$$

$$Energy = \sum_{i,j=0}^{N-1}\left(P_{ij}\right)^2$$

$$Homogeneity = \sum_{i,j=0}^{N-1}\frac{P_{ij}}{1+(i-j)^2}$$

These features are calculated with distance 1 and angle 0, 45 and 90 degrees.

2.3 K-Means Clustering

A cluster is a collection of data objects that are similar to one another with in the same cluster and are dissimilar to the objects in the other clusters. It is the best suited for data mining because of its efficiency in processing large data sets. It is defined as follows:

The k-means algorithm is built upon four basic operations:

1. Selection of the initial k-means for k-clusters.
2. Calculation of the dissimilarity between an object and the mean of a cluster.
3. Allocation of an object of the cluster whose mean is nearest to the object.
4. Re-calculation of the mean of a cluster from the object allocated to it so that the intra cluster dissimilarity is minimized.

The advantage of K-means algorithm is that it works well when clusters are not well separated from each other, which is frequently encountered in images. The cluster number allotted to each image is considered its class or group.

2.4 Similarity Matching:

Many similarity measures have been developed for image retrieval based on empirical estimates of the feature extraction. We have used Euclidean Distance for similarity matching.

The Euclidean distance between two points $P = (p_1, p_2, \ldots, pn)$ and $Q = (q_1, q_2, \ldots, q_n)$, in Euclidean n-space defined as:

Now for the retrieval purpose the user select the query patch and on the basis of its class number the distance between the query patch with the other images of that class is calculated and images are retrieved.

III. Experimental Plan

For our experiments, we use 3 LISS III + multi-spectral satellite images with 23.5m resolution. We choose to support 4 semantic categories in our experimental system, namely mountain, water bodies, vegetation, and residential area. In consultation with an expert in satellite image analysis, we choose near-IR (infra-red), red and green bands as the three spectral channels for classification as well as display. The reasons for this choice are as follows. Near-IR band is selected over blue band because of a somewhat inverse relationship between a healthy plant's reflectivity in near-IR and red, i.e., healthy vegetation reflects high in near-IR and low in red. Near-IR and red bands are key to differentiating between vegetation types and states. Blue light is very abundant in the atmosphere and is diffracted all over the place. It therefore is very noisy. Hence use of blue band is often avoided. Visible green is used because it is less noisy and provides unique information compared to Near IR and red. The pixel dimensions of each satellite image are used in our experiments are 720x540, with geographic dimensions being approximately 51.84Km×38.88Km. The choice patch size is critical. A patch should be large enough to encapsulate the visual features of a semantic category, while being small enough to include only one semantic category in most cases. We choose patch size 100×100 pixels. We obtain 80 patches from all the images in this manner. These patches are stored in a database along with the identity of their parent images and the relative location within them. Ground truth categorization is not available readily for our patches.

The four major classifications of images are shown in figure 2 to 5. Figure 6 and 7 shows the content based retrieval system. We get 80% to 83% accuracy in our results.

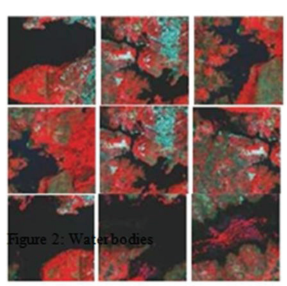

Figure 2: Water bodies

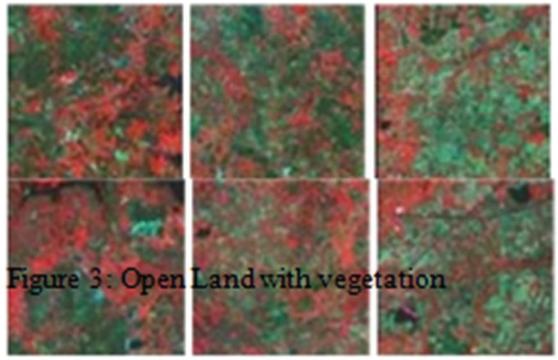

Figure 3: Open Land with vegetation

Figure 4: Buildings

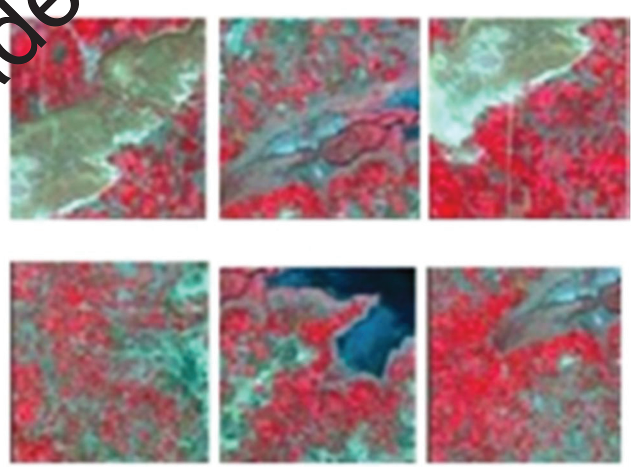

Figure 5: Vegetation and Mountain

Figure 6: CBIR System

Figure 7: Screen 2 of CBIR System

IV. Conclusions

For retrieving similar images to a given query image we have developed a prototype system. We get fruitful results on the example images used in the experiments. We can use this technique for mining similar images based on content and knowledge base for finding vegetation or water or building areas.

V. References

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