

# Remote Sensing Image Retrieval using Semantic Mining

Deepti Jhaman Punjabi, Ajitkumar Khachane, Ranjana Gite

**Abstract**— Understanding of images continues to be one of the most exciting and rapidly-growing research areas in various fields of technology. The recent advancements in hardware and telecommunication technologies like satellite communication in combination with the ongoing web proliferation have boosted growth of digital visual content on a large scale. However, this rate of growth has not been matched by the simultaneous improvement of technologies to support efficient image analysis and their retrieval. As a result, the overflow of available visual content resulted in large number of users facing hindrance in accessing information of the appropriate visual content. Moreover, with the immense number of diverse application areas that have emerged, which rely solely on image processing systems, has further revealed the tremendous potential for effective use of visual content through intelligent analysis. Better access to image databases, enhanced surveillance and authentication support systems, content filtering, adaptation and transcoding services, improved human and computer interaction, etc. are among the several application fields that can benefit from semantic image analysis or semantic mining. In this, images from desired database have been subjected to various steps involved in processing of images like pre-processing, segmentation, region level feature extraction and semantic mining. Satellite images are used to monitor the remotely sensed geographic area under consideration. Pre-processing involves steps where low level features are easily obtained using content based image retrieval scheme. Semantic mining technique is used to obtain other high level features for better image retrieval. Furthermore, region based segmentation allows systematic decoding of visual information and quantization based on different color intensities involved in the image. In this segmentation is performed based on the proposed JSEG (J Segmentation) algorithm. A probabilistic method will be used to mine the relationship among semantic features, regions, and images for region based feature extraction. Finally the Expectation Maximization method is used to analyze the relationship and extract the latent semantic concepts. This involves implementation of this approach on a dataset consisting of thousands of satellite images to obtain a high retrieval precision, thus solving our purpose.

**Keywords**- Segmentation, image retrieval, object-based image analysis, remote sensing (RS) image,

## I. INTRODUCTION

Remote sensing has turned out to be one of the major research applications of image processing domain. Images obtained from the satellites cover huge geographical area like water bodies, forests, urban areas and many more.

Manuscript published on 30 October 2014.

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The information in remotely sensed images plays an important role in environmental monitoring, disaster forecasting, geological survey, and other applications. With the continuously expanding demand for remotely sensed images, many satellites have been launched, and thousands of images are acquired every day. This leads to steadily increasing database of these remotely sensed images which makes it difficult for extraction of important information from them. Thus retrieval of useful images from unstructured database is a challenge. Conventional image query processes involve matching keywords such as geographic location, sensor type, and time of acquisition. In order to overcome shortcoming of these techniques, image retrieval techniques are strongly focused on content-based image retrieval (CBIR) where low-level features are used to represent image content and retrieve image from database, such as spectrum, texture, and shape. [1] Although many achievements have been accomplished, visual-feature-based CBIR is known to have a limited capability because human image interpretation has been found to be highly semantically related. It not only depends on image visual features' but also on an individual's understanding and judgment originating from his/her experiences.[2] Semantic features are high level hidden concepts of an image. The difference between low-level features and high-level concepts is called 'Semantic Gap' which can be bridged by using semantic feature mining based image retrieval technique. This technique is divided into steps: Low-level feature extraction and high-level semantic feature extraction. Semantic feature extraction shall be performed using the proposed JSEG algorithm. Further in this research few mathematical steps might be incorporated to analyze the relationship and extract the latent semantic concepts.

## II. REVIEW OF RELATED WORK

During the last decade many approaches have been proposed to retrieve satellite images using their content. Ma and Manjunath have designed region-based image-retrieval systems where the similarity between two images was measured based on individual region-to-region similarity and later extended to image-to-image similarity based on all segmented regions within the scenes [9]. Li et al. have retrieved satellite images after classification into a predefined semantic concepts as cloud, water, forest, urban area, farmland, bare soil and rock using grayscale images [10], or using multispectral isolated images [11], [8], [12]. Ferencat and Boujemaa retrieved six predefined classes as city, cloud, desert, field, forest, and sea from isolated images and ground truth database [13]. Lei Niu et al. have used multi-band isolated JPEG2000 coded images to retrieve area of interest depending on query image using hue saturation and value color model conversion [14].



Tuia et al. have adopted a satellite images classifier using active learning in high resolution hyperspectral images [15]. Blanchart et al. have developed a system which combines the auto-annotation systems and the category search engines [16]. Although all the previous work has taken satellite image as the matter of interest, it did not take into account:-

The continuous nature of satellite cover and the geospatial relationships between different satellite images.

The multiple hierarchy of frame work based on the adjacent area to first stage candidates and irregular shape

### III. PROBLEM DEFINITION AND PROPOSED WORK

Semantic feature mining is essential to semantic-based image retrieval technique. High-level feature extraction is normally based on pixel-level features which is insufficient to obtain semantic data. This proposal deals with grouping of similar pixels to form a region so that a region-level image content description can be obtained to facilitate users' understanding of image. The research further aims at developing some correlation between images, region and hidden semantics. The proposed method is divided in following steps:

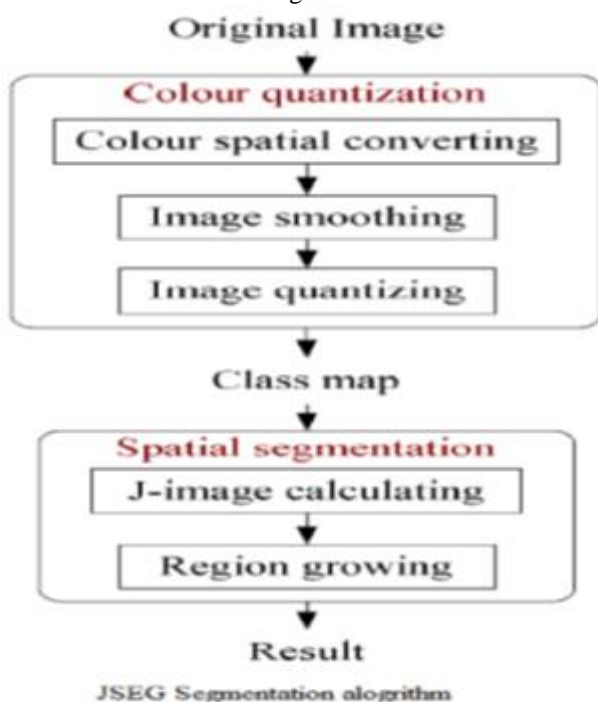
**A) Building up of database:**

Database to be obtained from existing satellite images of the target region.

**B) Preprocessing and segmentation using JSEG algorithm.** Can be classified into 2 steps:

- Color quantization
- Segmentation

**Color Quantization:** Color quantization is a process that reduces the number of distinct colors used in an image, usually with the intention that the new image should be as visually similar as possible to the original image. The flow is shown as below in Fig.1.



**Fig.1**

**Segmentation:** In image segmentation, region growing method is proposed for region based segmentation. Here regions can be divided depending on their threshold values which control region growing result.

**C) GLCM**

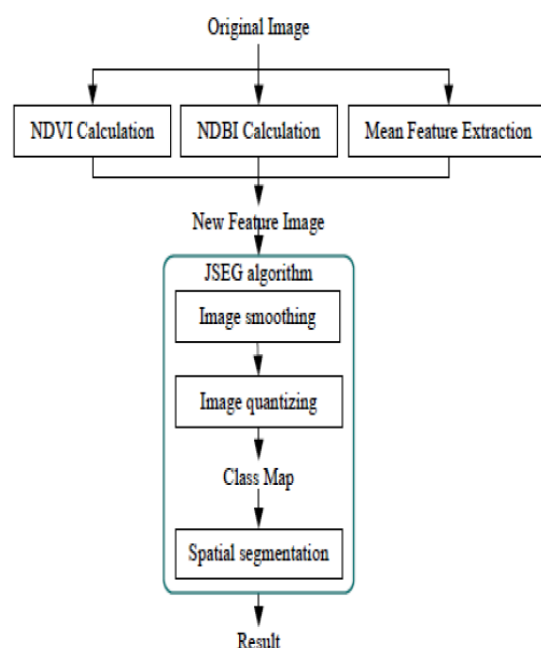
Representation of regional information is usually done by using spectral and texture features which can be extracted using this proposed algorithm. This technique involves comparison of different grey levels of image to decode the required feature information.

**D) Code Book Extraction**

Further in this research there will be grouping of images to form regions which can be stored in a database called codebook. Similarities between spectral and textural features will be analyzed and tested. After the images have been segmented into several parts, a number of regions are generated and stored in the database. It will be time-consuming to calculate the similarity between two regional features for all pairs of regions. However, many regions on different images are very similar in terms of spectral and textural features. Therefore, GLA is used to classify the low-level features into a set of codes based on which a codebook will be generated.

**E) Semantic Feature Extraction**

This step will include mathematical steps to obtain relationship among semantic features, regions, and images automatically. Then proposed Expectation Maximization method will be used to analyze the relationship and extract the latent semantic concepts as shown in Fig 2.



**Fig.2.**



In this step, a probabilistic method is used to mine the relationship among semantic features, regions, and images automatically. Then the EM method [28,29] is used to analyze the relationship and extract the latent semantic concepts.

First, various parameters are defined as follows:

(a) Image data:  $d_j$  is an image in the database,  $d_j \in \{d_1, \dots, d_M\}$ ;  $M$  is the total number of images.

(b) Regional feature data:  $r_i$  is the  $i$ th region feature in the feature codebook,  $r_i \in R = \{r_1, \dots, r_N\}$ , where  $N$  is the total number of regional features.

(c) Hidden semantic features:  $s_k$  is the hidden semantic feature,  $s_k \in S = \{s_1, \dots, s_K\}$ , where  $K$  is the total number of semantic features.

where  $j$  is the number of images,  $j \in \{1, \dots, M\}$ ;  $i$  is the number of region features,  $i \in \{1, \dots, N\}$ ;  $k$  is the number of semantic features,  $k \in \{1, \dots, K\}$ .

$P(d_j)$  denotes the probability that an image will occur in a particular image database.  $P(r_i|s_k)$  denotes the class-conditional probability of region  $r_i$  given the hidden semantic feature  $s_k$ .  $P(s_k|d_j)$  denotes the class-conditional probability of the hidden semantic feature  $s_k$  given a particular image  $d_j$ .  $d_j$  and  $r_i$  are independently defined on the state of the associated hidden semantic feature. According to conditional probability formula, the joint probability of  $d_j$  and  $r_i$  can be described by Equation (1)

$$P(r_i, d_j) = P(d_j)P(r_i|d_j) \quad (1)$$

Then, applying total probability formula, Equation (1) can be transformed to Equation (2):

$$P(d_j) P(r_i|d_j) P(s_k|d_j) \quad (2)$$

The class-conditional probability of semantic feature  $s_k$ ,  $P(s_k|r_i, d_j)$ , depends on image  $d_j$  and region feature  $r_i$ . Using the Bayesian formula, this class-conditional probability can be described by Equation (3)

$$P(s_k|r_i, d_j) = P(r_i, d_j|s_k) / P(s_k)P(r_i, d_j) \quad (3)$$

Since  $d_j$  and  $r_i$  are independent, referring to Equation (2), Equation (3) can be transformed to

$$P(s_k|r_i, d_j) = P(d_j|s_k) P(r_i|s_k) P(s_k) / P(d_j) P(r_i|s_k)P(s_k|d_j) \quad (4)$$

where  $l$  is the number of semantic features,  $l \in \{1, \dots, K\}$ .

Referring to Bayesian formula, Equation (4) can be transformed to

$$P(s_k| r_i, d_j) = P(r_i|s_k)P(s_k|d_j) / P(r_i|s_l)P(s_l |d_j) \quad (5)$$

Then, referring to the likelihood principle,  $P(d_j)$ ,  $P(r_i|s_k)$  and  $P(s_k|d_j)$  can be determined by maximizing the log-likelihood function:

$$L = \log (P(R, D, S)) = \sum_{(r_i, d_j)} \sum_{(s_k|r_i, d_j)} n(r_i, d_j) \log [ P(s_k|d_j) P(r_i|s_k) ] \quad (6)$$

where  $n(r_i, d_j)$  indicates the number of occurrences of region  $r_i$  in image  $d_j$ .

The standard procedure for maximum likelihood estimation is the EM algorithm. This method has two steps: expectation step (E-step) and maximization step (M-step). The E-step can be interpreted as mining the relationship between current estimates of the parameters and the latent variables by computing posterior probabilities. The M-step can be interpreted as updating parameters based on the so-called expected complete-data log-likelihood.

According to the EM method, the process of obtaining Equation (4) can be considered as the E-step, and the process of obtaining Equation (5) can be considered as the process of log-likelihood estimation. Then, Equation (5) is maximized using Lagrange multipliers. Equations (7) and (8) can then be derived

$$P(r_i|s_k) = n(r_i, d_j)P(s_k|r_i, d_j) / \sum_{(r_m, d_j)} n(r_m, d_j) P(s_k| r_m, d_j), \quad (7)$$

$$P(s_k|d_j) = \sum_{(r_i, d_j)} n(r_i, d_j)P(s_k|r_i, d_j) / \sum_{(r_m, d_j)} n(r_m, d_j) \quad (8)$$

where  $n$  is the number of regions and region features,  $n \in \{1, \dots, N\}$ .

The E-step and M-step equations are calculated alternately until a local maximum of the expectation in Equation (9) is found. Because the distributions of  $P(R|S)$ ,  $P(S|D)$ , and  $P(S|R, D)$  are uniform, their initial values can be set equal to  $P(R|S)$ . The number of iterations depends on experience; in this research, it is set to five. Each image can then be represented by the posterior probability  $P(s_k|d_j)$  instead of by the original image feature.

#### IV. JSEG Segmentation

Color images with homogeneous regions are segmented with an algorithm to generate clusters in the color space/class (different measures classes in spectral distribution, with distinct intensity of visible electromagnetic radiation at many discrete wavelengths) [21]. One way to segment images with textures is to consider the spatial arrangement of pixels using a region-growing technique whereby a homogeneity mode is defined with pixels grouped in the segmented region.

Furthermore, in order to segment texture images one must consider different scales of images. An unsupervised color-texture regions segmentation algorithm is ideal for this purpose, since it tests the homogeneity of a given color-texture pattern, which is computationally more feasible than model parameter estimation. It deals with the following assumptions for the acquired image: \_ Image containing homogeneous color-texture regions; \_ Color information is represented by quantized colors;



Colors between two neighboring regions are distinguishable. The JSEG algorithm segments images of natural scenes properly, without manual parameter adjustment for each image and simplifies texture and color. Segmentation with this algorithm passes through two major stages, namely color space quantization (number reduction process of distinct colors in a given image), and hit rate regions with similar color regions merging, as secondary stage.

In the first stage, the color space is quantized with little perceptual degradation by using a quantization algorithm [18] [19] with minimum coloring. In this context, each color is associated with a class and the original image pixels are replaced by classes to form the class maps (texture composition) for the next stage. Before performing the hit rate regions, the J-image - a class map for each windowed color region, whose positive and negative values represent the edges and textures of the processing image - must be created with pixel values used as a similarity algorithm for the hit rate region. These values are called "J-values" and are calculated from a window placed on the quantized image, where the J-value belongs. Therefore, the two-stage division is justified through the difficult analysis of the colors similarity with their distributions. The decoupling of these features (color similarity and spatial distribution) allows tractable algorithms development for each of the two processing stages (Fig.3).

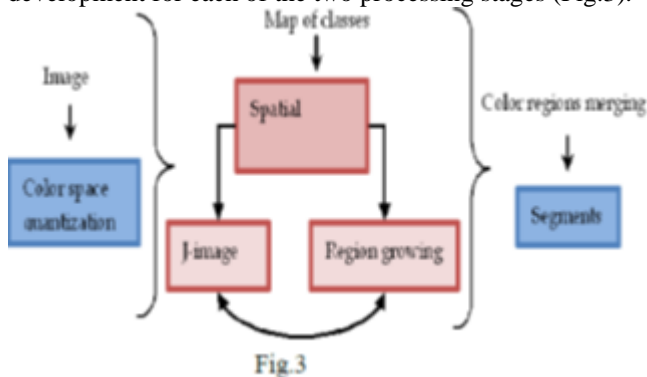


Fig.3

## V. Future Work and Conclusion

In this paper we have proposed a framework to achieve semantic-based retrieval in remote sensing archives. A new method is provided to identify the optimal classes number in feature classification. For future work, we will explore knowledge based feature classification to provide a more accurate segmentation in remote sensing images.

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