Comparative Study of Content Based Remote Sensing Image Retrieval Using Texture Descriptor

* S.Suganya, ** J.Rethna Virgil Jeny, M.E,(Ph D) , **R.Raja Sekar, M.E.,
*PG Scholar, **Asst. Prof
Department of Computer Science Engineering
Sardar Raja College of Engineering, India

Abstract:

Remote sensing image retrieval is the tedious process because the capacity of image acquisition is increasing and the size of the remote sensing database is also increasing. In this paper we are going to compare numerous techniques which effectively retrieve the high resolution remote sensing images from the large remote sensing archives with new powerful multi-scale texture descriptors namely circular covariance histogram (CCH) and the rotation-invariant point triplets (RITS). To enhance effectiveness of image retrieval we are utilizing Fourier power spectrum of the quasi-flat-zone-based scale space of their input. UC Merced Land Use–Land Cover data set is used for evaluating the descriptors which is recently made public.

Key terms: Remote sensing, Texture descriptors, Morphological operators, content based image retrieval (CBIR).

1. Introduction

Content-based image retrieval research is lively discipline they are concentrating on solving the hard problems. In [1] CBIR also known as query by image content and content visual information retrieval is the application of computer vision techniques which solve the problem of image retrieval. "content-based image retrieval" is used for automatic retrieval of images from a database. Figure(1) illustrate the Frame work of RS image retrieval. It places an important role in retrieving image from the remote sensing database because of the development in Earth Observation System. Forecasting and research oriented quantity of the remote sensing database is increasing dramatically, which leads the retrieval technique for remote sensing images gradually becomes the urgent problem. In [2] [6] Content based denotes the analysis takes place on the bases of content of an image not its metadata such as keywords, tags etc associated with the image. It is important to use it effectively to get the needed information for the given task.

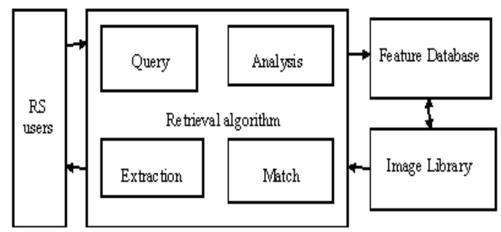

Figure (1) The framework of content-based RS image retrieval

To get the needed information in mass image database and retrieving it effectively, selection of effective and robust similarity measure has been the bottleneck of mass database management. In [3] there are different modes of retrieval like Retrieval based on mask, Retrieval based on attribute, Retrieval based on description information, Retrieval based on semanteme, integrated retrieval mode. Normally the image has the higher amount of spatial and spectral details which leads to the new applications like hyperspectral target detection, compound object recognition etc and also leads to the use of a wider range of image analysis method. There are various descriptors like local descriptors even though they have the invariant capacities against rotation, illumination, and scale variations they have some limitations in retrieving the remote sensing images. In this paper we have described two texture descriptors such as circular covariance histogram and the rotation-invariant point triplets by using the Mathematical Morphological tool. They also use Fourier power spectrum of the quasi-flat-zone-based scale space of their input for improving the retrieval rate. This descriptor has been evaluated with the UC Merced Land Use–Land Cover (LULC) data set, to achieve the best retrieval score when compared with other approaches.

2. TEXTURE DESCRIPTORS

This section details with explaining the principles of CCH and RITS and also explains the two more texture descriptors based on the FPS of an image's QFZ representation.

2.1 Circular Covariance Histogram:

In [1] CCH colored image is converted into grey-scale image which is given as the input image. CCH examines the regular patterns in their input. Then the structuring element which is used to probe the image is formed in the circular manner. It is passed into the morphological operator T which includes Dilation, erosion, opening, closing and so on which gives the series of intermediate images which combine to form single label image which has the same dimension as the input image. Then it is normalized to form n-dimensional feature vector in the histogram form.

2.2 Rotation-Invariant Point Triplets (RITS):

In [1] RITs examine the regular patterns in their input like CCH. The input image is given as the grey-scale image but the structuring element is not taken in the circular form instead each circle is decomposed into the antidiametrical point triplets. Then the image is processed using the Morphological operator which gives the series of intermediate images and combines them to form the single label image that has the same dimension as the input image. Then they are normalized to form n-dimensional feature vector in the form of histogram like CCH, but the only difference is that the execution time is higher when compared to CCH.

2.3 FPSs from QFZs:

In [1] is implemented to overcome some of the limitations of CCH and RITs. Since they consider only the regular patterns in the image but in the remote sensing some complexities like coarseness and directionality should be considered. The Fourier power spectrum by using the quasi-flat-zone the coarseness and directionality of the image is considered for improving the retrieval accuracy and to reduce execution time. The main advantage of this algorithm is that it reduces the length of the feature vector and execution time.

3. Comparison With Different Descriptor

3.1 Color Descriptor

In [27] Color descriptor is one of the important factor in the image retrieval which consist of number of histogram descriptors, dominant descriptor and color layout descriptor in MPEG-7.Color histogram descriptor is mainly for color distribution which leads to the reasonable accuracy for image searching and retrieval but there are so many independent dimension in color histogram which leads to number of choice so it needs to limit the set of histogram derived descriptor like scalable color descriptor in hue-saturation-value(HSV). HSV aims at collection of pictures or group of frames from a video. The color structure histogram aims at identifying color distribution using structuring elements which is contracted in hue-min-max difference. Dominant color descriptor explains the distribution of salient colors in the image that is used to provide compact, effective and intuitive representation of color in the interested region. Color layout descriptor captures the special layout in the dominant color of the interested region which can be implemented for fast browsing and search of images. The disadvantage of color descriptor is that it is computationally a complex task to perform the operation over colors. Figure (2) illustrate the different color descriptors.

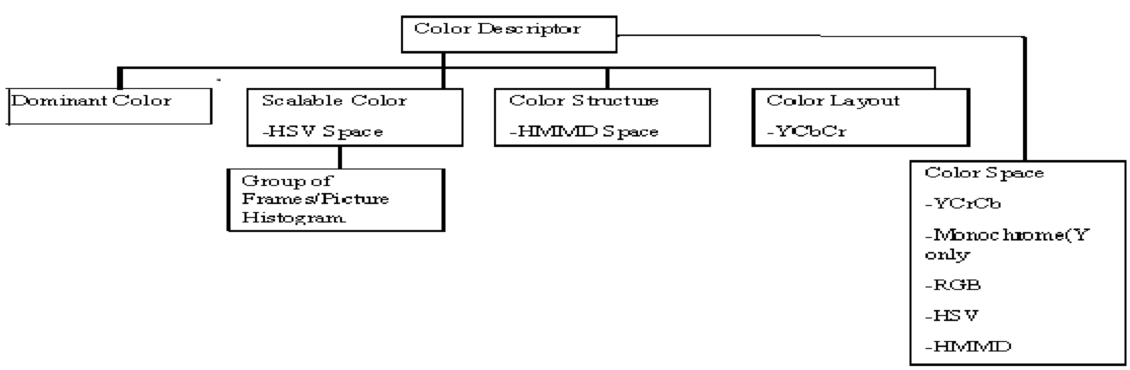

Figure (2) color descriptor

3.2 Texture Descriptor

In [27] Texture descriptor is one of the powerful tool in image retrieval in MPEG-7 which includes (i)texture browsing descriptor, (ii) homogeneous texture descriptor and (iii) local edge histogram descriptor. In texture browsing descriptor the attributes like directionality, coarseness and regularity are considered. Homogeneous texture descriptor helps in similarity retrieval using quantitative characterization of similar texture region that depends on the local spatial frequency statistics of textures. Local edge histogram is used only for the region which is not homogeneous in texture property. The disadvantage of this technique is that it can process only limited images.

3.3 Morphological approach

In [18] Morphological approaches deals with the multi-scale high resolution satellite imagery. It is suitable for the complex image scenes like aerial or fine resolution remote sensing images. It is also suitable for low diametric contrast and low spatial resolution which leads to textural effect, border effect and ambiguity in object or object ground. Morphological operator includes erosion, dilation, opening, closing, rank filters etc. In [23] this operator can be applied on binary or grey-scale images. In [4] recent Morphological approach remote sensing images are processed to remove salt and pepper noise thereby better space descriptor is achieved .The disadvantage of this approach is that it has the computational complexity because of increasing opening and closing range by reconstruction operator.

3.4 Grey-Scale and rotational invariant

In [26] Grey-scale and rotation invariant is simple and efficient. Multi- resolution approach for the grey scale and rotation invariant texture classification is done by local binary patterns. Grey-scale and rotation invariant approach is vigorous in terms of grey-scale variation because operator is invariant against monotonic transformation with the grey-scale. Grey-scale and rotation invariant detects the uniform patterns at any special resolution in the circular covariance of angular space that combines the multiple operators for multi resolution but the operator responses are independent. Advantage of this approach is that it is computationally simple because only few operations are performed in a small neighborhood and achieves the excellent experimental results.

3.5 Bags-of-Visual Words (BOV):

In [9] Classifying very high resolution aerial image is critical task because of the detailed information of spatial and texture. To overcome these problems bags of visual words algorithm is proposed. BOV contributes the following, first BOV is mainly used for representing and classifying the satellite imagery, second even the low level features are examined to obtain better performance, third a threshold is used to produce a virtual word which avoid misclassifying outliners. There are three different types of geospatial objects like simple object, complex object and composite object but BOV is used to unify the complex and composite object. The advantage of this approach is that it is used to understand geospatial object and low computational complexity. Figure.3 illustrate the BOV image-classification

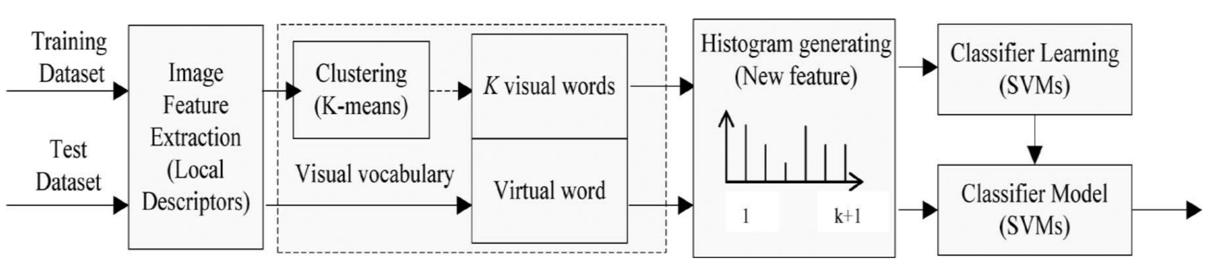

Figure (3) BOV image-classification approach.

3.6 Bayesian inference

In [15] Bayesian inference is used for interactive learning and probabilistic retrieval in content based remote sensing image collection. In this interactive approach they provide immediate update of the posterior map because of the instantaneous feedback to the user. In [12] Bayesian inference focus on content based query technique which includes the application specific interest and integration with user. This approach links the existing data mining and information system and also by combining distributor computing with interactive analysis and with various algorithm. The main advantages of Bayesian inference technique is that they won't have any adhoc assumption which makes it to perform robust processing of information and the same techniques is used to retrieve image in the probabilistic manner. The main disadvantage of this approach is that it includes the user interaction which is the time consuming process.

3.7 Scale Invariant features transformation (SIFT)

In [11] SIFT is proposed to overcome the problem of object recognition which need the image feature that distinguish a specific object from different alternative and also those features should be partially invariant to illumination, it should be unaffected by nearby clutter or partial collusion. Scale invariant feature transform on image with large number of local feature vector is invariant to all image translation, rotation and partially invariant to the illumination changes and 3D projection. SIFT are mainly computed for the normalized image patches. The illumination invariance is obtained by normalizing with the square root. This approach also describes the enhancement in indexing and model verification. This allows robust resignation in partial collusion. The main disadvantage of this approach is that it dealt with single view of 2D structure of the object and rigid deformation.

3.8 Query by example approach

In [7] Retrieving image from the professional remote sensing data base needs the information like location of scene, the utilized scanner, date of acquisition but this is not suitor for the user who have limited knowledge about remote sensing. To overcome this disadvantage this algorithm is proposed for retrieving satellite imagery. In this algorithm the researcher proposed the liable and scanner independence technique for feature extraction and representation. For feature extraction they used the weighted fuzzy expected value which is based on k-mean algorithm. Feature extraction and retrieval is done in the database which is the combination of urban, agriculture and forestry areas which has the multispectral scenes. This image collection covers the area more than 204.15 km. The main advantage of this paper is that it increases the insensitivity to noise and also it guarantees the high stability and reliability.

3.9 Similarity Measures

In [14] similarity measures are used to measure the similar degree between the multisource data which is the important technique of content based image retrieval. The first step in this approach is the feature extraction; general features like texture is extracted then converted into grey-scale image for further process. In image processing two basic histograms like frequency histogram and cumulative histogram are used. The similarity measure is one of the important problems in remote sensing image retrieval. It is measured by the distance between some features of the image. In [14] There are several types of similarity measures some of which are three of Minkowski distance measures and cosine of the angle measure, histogram intersection, center moment method, x^2 statistical distance measure and Bhattacharyya distance measure. This measure helps for the quicker retrieval of image for the large remote sensing database. The main disadvantage of this measure is that it won't consider the complexity in remote sensing images like coarseness and directionality.

3.10 Framework for Semantic Labeling

In [10] Identifying and labeling the image automatically is the tedious task. The present method is not efficient to capture complex object and their spatial relationship. To overcome this problem an algorithm framework for automatic sematic labeling of large image archive is proposed. This framework consist of segmentation feature extraction, vector quantization and Latent Dirichlet Allocation modules which is illustrated in the Figure (4). In **[40]** It helps in evaluating new feature and categories in large database.

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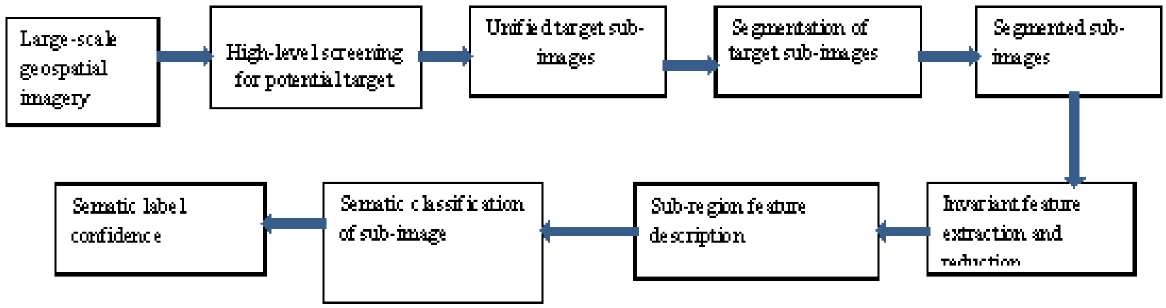

Figure (4) Frameworks for Semantic Labeling

3.11 Support Vector Machines (SVM):

In [16] the complexity of the scene of remote sensing images increase due to the increase in the resolution of the remote sensing image. To overcome this drawback support vector machine was proposed which provide two main enhancements in the remote sensing image retrieval. First it provides an optimized transfer between the user and the system though the selection of image by forwarding active learning selection criterion which minimizes redundancy between the user and the image shown to them. Second to overcome the low retrieval performance due to high sensitivity, this approach introduces insensitivity to scale for achieving the desire retrieval performance by using specific kernel function. The advantage of this approach is that it reduces the sematic gap by elimination search on several consecutive retrieval rounds instead the user provides feedback at each retrieval round. The disadvantage is that increased time complexity due to continuous user feedback.

3.12 Entropy Balanced Bitmap (EBB)

In [8] GeoIRIS contains 45 GB of high resolution satellite imagery which is very difficult to store, maintain and retrieve those high resolution images. To overcome these difficulties EBB approach is proposed which automatically extract image from remote sensing database and shape encoding compresses their total size of the shape descriptor to about 0.34% of the database size. This approach gives the probabilistic nature of bit values in derived shape by itself. The advantage of this approach is that it leads to fast retrieval of remote sensing image for the large database which may contain about 1.3 million objects.

3.13 Hit or Miss Transformation (HMT):

In [5] HIT is mainly proposed for identifying the buildings by overcoming the difficulties faced by the traditional methods of detecting building in high spatial resolution multispectral images. The buildings are detected using contextual and spectral information. First spectral similarities between the roofs are identified using the similarity ratio and from mathematical morphology is applied to assign pixels to building using the techniques like fuzzy erosion and dilation, additional processing is needed for separating building form road . This approach provides the reliable building detection technique.

3.14 Binary Partition Tree (BPT):

In [22] The remote sensing sector has many practical applications and there are some challenges in terms of image processing that is the spatial correlation between the pixels and also spectral correlation between spectral brands are not considered in the traditional methods which are important factors. BPT is very malleable approach since it is applied to any type of images especially radar and optical images are experimented in this approach and also BPT can be used for different applications like filtering, segmentation, classification etc. radar remote sensing technology is growing significantly but there are more challenges in it which is overcome by this binary partition tree approach.

4. Comparison:

Remote sensing image retrieval performance is compared with different algorithms which is shown in the table

Comparison Table

ALGORITHM		RETRIEVAL PERFORMANCE (%)
Similarity Measures [14]	Euclidean distance	83.3
	City-block distance	87.92
	Dominance distance	79.17
	Cosine of the angle	84.58
	Histogram intersection	87.92
	x2 statistical distance	89.17
	Center moment	61.67
	Bhattacharyya distance	72.50
Morphological Approach [19]	DAFE	97.2
	DBFE	96.6
	NWFE	95.8
Local Binary Patterns [26]		95.2
SIFT [11]	Increase contrast by 1.2	89.0
	Decrease intensity by 0.2	88.5
	Rotate by 20 degrees	85.4
	Scale by 0.7	85.1
	Stretch by 1.2	83.5
	Stretch by 1.5	77.7
	Add 10% pixel noise	90.3
Binary partition tree [22]		94.69

5. Conclusion:

There are many approaches for performing effective retrieval in the remote sensing images, in that most of the methods they don't consider the complexity of remote sensing images like coarseness and directionality which is the most important factor to be considered. In FPS coarseness and directionality of the image is consider for achieving the best retrieval score and it has reduced execution time. But this approach focuses only on frequency domain. In future the time domain may be considered.

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S.Suganya received her B.E degree in Information Technology from Avinashilingam University, Coimbatore in 2008 and MBA degree in Finance and Marketing from Bharathiar University, Coimbatore in 2010. She is currently doing M.E in Computer science and Engineering at Anna University, chennai. Her Area of interest includes CBIR in image processing.

J.Rethna Virgil Jeny received her B.E and M.E degrees in Computer Science and Engineering from Bharathidasan University, Trichy in 1997 and Annamalai University in 2005 respectively. She is currently doing Ph.D in wireless sensor Networks at MS University. She has received Lady Engineer Award by IEI. She is a member of IEEE, ACM, ISTE, IEI, IAENG and a senior member of IACSIT. Her research interests include Energy aware routing and Cross layer routing in Wireless Sensor Networks.

R.Raja Sekar received the B.E Degree in Computer Science and Engineering from Anna University, Chennai in 2010 and received M.E Degree in Computer Science and Engineering from Anna University. His area of interest is Digital image processing and Biometrics.