HIERARCHICAL SEGMENTATION OF IMAGES USING GRAPH LAPLACIAN ENERGY: A SURVEY

P.Kavitha[1]/PG Scholar, S.Vinoth kumar [2]/Assistant Professor, S.Karthik[3]/Prof&Dean
Department of Computer Science & Engineering
SNS College of Technology,
Coimbatore, India
[1]kaviaze@gmail.com
profvinoth123@yahoo.co.in
[3]profkarthik@gmail.com

Abstract- **Image Mining is the process of semi automatically analyzing the large database to find useful patterns. Image mining technology has been considered an advanced field for discovering information related to the images. The demand of image mining increases as the need of image data is growing day by day. There are many techniques developed in the earlier researches and eventually these techniques can reveal useful information according to the human requirements, but Image Mining still require more development especially in the area of web images. Image mining task can also be categorized into classification, clustering, association rule mining, and characterization based summarization. This paper presents a survey on various image mining techniques.**

Keywords: **Image Mining, Segmentation, Classification, Clustering.**

I. INTRODUCTION

Image Mining is an extended branch of data mining that is concerned with the process of knowledge discovery concerning images. Image Mining deals with the extraction of image patterns from a large collection of images. In Image Mining, the goal is the discovery of image patterns that are significant in a given collection of images. Image Mining deals with extraction of knowledge, image data relationship and other required patterns and uses ideas from image processing, image retrieval and machine learning, databases. The focus of image mining is on the extraction of knowledge patterns from a large collection of images. While there seems to be some overlap between image mining and content-based retrieval, image mining goes beyond the problem of retrieving relevant images. In image mining, the goal is to discover image patterns that are significant in a given collection of images and the related alphanumeric data. The fundamental challenge in image mining is to reveal out the knowledge relating to the images from the web pages.

Preprocessing:

In image data, the spatial segmentation can be done at region and/or edge level based on the requirements of the application. It can be automatic or manual and should be approximate enough to yield features that can reasonably capture the image content.

Feature Extraction and Transformation:

Color, edges, shape, and texture are the common image attributes that are used to extract features of mining. Feature extraction based on these attributes may be performed at the global or the local level. There are obvious trade-offs between global and local descriptors. Global descriptors are generally easy to compute, provide a good representation, but they tend to integrate and therefore are often unable to discover subtle patterns or changes in shape. Local descriptors, on the other hand, tend to generate more elaborate representations and can yield useful results even when part of the underlying attribute.

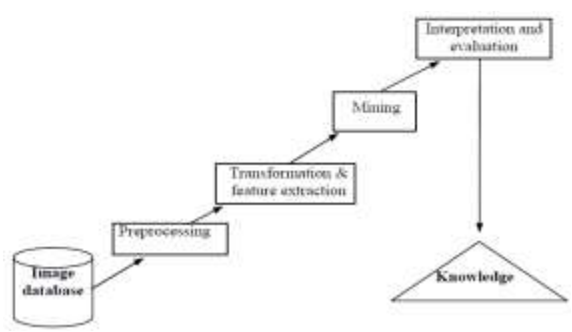

Figure 1: Basic steps in image mining

II. LITERATURE SURVEY

1) Automatic Detection of Geospatial Objects Using Multiple Hierarchical Segmentations

Segmentation algorithm combines spectral information from the original data with structural information extracted through morphological operations. A generic iterative algorithm is used to extract meaningful segments from this hierarchy by simultaneously optimizing spectral homogeneity and neighborhood connectivity. New method is proposed for unsupervised image segmentation and automatic object detection in high-resolution remotely sensed imagery. Our segmentation algorithm exploited structural information using morphological operators. These operators were applied to each spectral band separately, where candidate segments were extracted by applying connected components analysis to the pixels selected according to their morphological profiles. We evaluated the proposed approach qualitatively on three data sets. The results showed that our method that considers morphological characteristics, spectral information, and their consistency within neighboring pixels is able to detect structures in the image which are more precise and more meaningful than the structures detected by two popular approaches that do not make strong use of neighborhood and spectral information jointly. Object detection algorithm is proposed that formulate the detection process as an unsupervised grouping problem for the automatic selection of coherent sets of segments corresponding to meaningful structures among a set of candidate segments from multiple hierarchical segmentations obtained from individual spectral bands. The grouping problem was solved by using the PLSA algorithm that built object models by learning the object-conditional feature probability distributions. The automatic labeling of a segment was done by comparing its spectral and textural content distributions with the distribution of the learned object models. The object detection algorithm is generic in the sense that any model for a segment's content can be used by the grouping algorithm. Extensive performance evaluation showed that the proposed methods are able to automatically detect and group structures belonging to the same object classes.

2) Hierarchical Texture-Based Segmentation of Multiresolution Remote-Sensing Images

A new algorithm is proposed for the segmentation of multi resolution remote-sensing images, which fits into the general split-and-merge paradigm. The splitting phase singles out clusters of connected regions that share the same spatial and spectral characteristics. These clusters are then regarded as atomic elements of more complex structures, particularly textures that are gradually retrieved during the merging phase. The whole process is based on a recently developed hierarchical model of the image, which accurately describes its textural properties. It is completely unsupervised, with just a few parameters set at the beginning, and its final product is not a single segmentation map but rather a sequence of nested maps which provide a hierarchical description of the image, at various scales of observations. The high resolution of such images are given and the consequent presence of complex structures and textured areas the whole algorithm is based on the use of a recent hierarchical image model that enables the efficient and accurate description of textures. The main strength of the algorithm is its ability to reliably identify complex textured areas comprising elementary segments with completely different spectral characteristics and to provide segmentation products that are very close to the perception of a human interpreter. The algorithm provides a sequence of nested segmentation maps rather than a single map, allowing the image analysis at various scales of observation, which can be useful for a wide variety of applications. The choice to use only PAN data for the initial segmentation step allows us to better preserve fine details and structures and, together with the use of a tree-structured segmented, guarantees a reasonable processing time.

3) Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery

Pixel-based classification methods are not suitable for the VHR image. An alternative solution is to incorporate as much information on spatial neighbourhood properties as possible into the classification process. Object-based classification has been proposed as a means of incorporating such spatial information into the classification procedure. The object based methods involve two steps: segmentation and classification. In the segmentation stage, the major task is to partition the whole image into a series of closed objects, which coincide with the actual spatial pattern. Three different classification methods were investigated: maximum likelihood classification (MLC) at the pixel level, nearest neighbor (NN) classification at the object level, and a hybrid classification that integrates the pixel and object-based methods (MLCNN).

a. *Maximum likelihood classification (MLC) at the pixel level*

spectral separability would be enhanced by taking the object as the basic unit as opposed to the pixel. Bhattacharya Distance (BD) is choosen to measure between-class separability. BD was calculated between two classes at a time by using their means and covariance matrices with the assumption that the two classes are in Gaussian distribution.The larger the BD value is, the better the final classification will be.

b. Object-based classification

Object-based classification began with a segmentation of the whole scene into closed objects. Starting from each seed point, at each step, a pair of neighbouring image objects will be merged into one large object. The scale parameter is an abstract value that determines the maximum possible change of heterogeneity caused by fusing several objects. There are unlimited choices of scale parameters. The final decision of scale parameter is often made by an interpreter based on our visual inspection of the image, rather than quantitative criteria. It is also very time consuming to conduct classification with all the possible scale parameters.

c. A new method to choose an optimal scale parameter in segmenting homogeneous objects

The nearest neighbor classifier is applied based on the same set of training samples that were applied in MLC. First, a feature space was defined in which each image object becomes a point. Since the training samples of each class occupy a spatially clustered location, the final assignment of an object will go to the class that has the sample nearest to the object in the given feature space.

d. Integrating pixel and object-based (MLCNN) methods

Combination of a pixel and object-based method would achieve the best classification accuracy. Maximum likelihood classification is performed first at the pixel level by merging the spectrally inseparable classes to one class. Those classes with good separability were then masked out and only spectrally mixed classes were further investigated with the object-based classification. Among the three classification methods, MLCNN achieved the best average accuracy of 91.4%.

4) *Multiscale representation and segmentation of Hyperspectral imagery using geometric partial Differential equations and algebraic multigrid methods.*

The multiscale/scale-space representation is obtained by solving a nonlinear diffusion Partial Differential Equation (PDE) for vector-valued images.

A.Nonlinear diffusion for hyperspectral imagery

The classical nonlinear diffusion PDE for vector-valued images are taken. The scale space by a parabolic PDE can be seen as a continuous transformation of the image into a space of progressively “smoother” images. Adequate selection of the scale reduces nuisance variability in the image and they obtained the best classification accuracies with this method.

B. Algebraic Multigrid Methods

Classic iterative methods reduce efficiently the high frequency components of the error, although they are extremely inefficient to reduce the low frequency components. Multigrid methods aim to reduce the error at all frequencies, in linear time complexity. Multigrid includes two complementary processes: relaxation and coarse-grid correction. Coarse-grid correction involves transferring information from a fine to a coarse grid via a sampling operation.

C. Segmentation of Hyperspectral Imagery

It is Proposed to form well-founded scale-space representation of an image using geometric PDEs, with a modified version of the AMG-based segmentation algorithm that naturally fits within this framework. The segmentation problem can be cast into the problem of graph partitioning. An image can be represented by a graph. Achieved image segmentation in linear time complexity, and it is often better than those obtained with normalized cuts. Multiscale representation of the image is constructed, statistics can be computed recursively from the different regions in the image.

Amg-based scale-space representation and segmentation of hyperspectral imagery

AMG requires the construction of a multigrid structure that starts with the finer grid of the original image on its base and coarser grids are added “below it” forming an inverted pyramid.

A. Multigrid Structure

The construction of the multigrid structure requires two main steps: selection of the next set of vertices from the current grid and the connection of the nodes. The mechanism used to select which vertices is a greedy strategy.

The selection process consists of the following three steps,

i. Sort in decreasing order of mass the set of vertices.
ii. Initialize the first element in the ordered set.
iii. vertex is independent of the vertices selected.

B. *AMG Solver*

It achieves the best rates of convergence for AMG using an implementation that on the finest grid corresponds to a Symmetric-Red-Black GS, while on the other grids we alternate the order of relaxation as we did on the finest grid, but based only on the order assigned by the sorting algorithm.

C. *Segmentation Algorithm*

This approach actually works reasonably well, and it is very flexible, since we use the same parameters to solve the PDE and to segment the image. A better approach is to solve the PDE and then segment the smoothed image using different parameters to construct the final multigrid structure. AMG structure is created over the smoothed image that stops the coarsening process when all the vertices are segment representatives.

5) *Region-Based Classification of Polarimetric SAR Images Using Wishart MRF*

The scattering measurements of individual pixels in polarimetric SAR images are affected by speckle so performance of classification approaches is damaged. A new classification method is introduced called Markov random field (MRF). In this method, an image is over segmented into a large amount of rectangular regions first. Then, to use fully the statistical a priori knowledge of the data and the spatial relation of neighboring pixels, a Wishart MRF model, combining the Wishart distribution with the MRF, is proposed, and an iterative conditional mode algorithm is adopted to adjust over segmentation results so that the shapes of all regions match the ground truth better. Finally, a Wishart-based maximum likelihood, based on regions, is used to obtain a classification map.

A. *WMRF-Based Over segmentation*

An image is segmented into a large amount of rectangular regions, not overlapping each other. It is called hard over segmentation. The Wishart distribution is a proper model for representing the statistical characteristic of the covariance matrix of a polarimetric SAR image. Based on the WMRF, the MAP criterion and the ICM algorithm are used to adjust iteratively the hard over segmentation result. The adjustment procedure is called soft over segmentation. After the soft over segmentation, few regions, which are not neighboring, have the same class label. They are regarded as one region for convenience in implementation.

B. Wishart-Based ML

For the supervised ML, the class labels of elements are determined by the statistical model and distribution parameters of training data. According to the Wishart distribution of the covariance matrix it can be derived. The classification performance of ML can be improved by iteration.

C. Procedure of the Proposed Method

The procedure of the proposed classification method for polarimetric SAR images using the WMRF-based segmentation is as follows:

i. over segmentation using WMRF

Set 0 for iteration number and calculate the average covariance matrix after few iterations performed. Then obtain the label. Finally check the condition to end iteration or repeat the steps.

ii. classification using Wishart-based ML

Set 0 for iteration number and calculate the mean and covariance by taking regions as elements. Finally check the condition to update the distribution parameters or end the iteration.

III. CONCLUSION

In this paper we have seen about few image mining algorithms and techniques used to mine the images. Each has both advantages and disadvantages. Finally, I conclude that Hierarchical segmentation method using graph Laplacian energy is efficient technique to segment the images and local self-similarity feature is used to capture the layouts of regions in an image and it yields Better performance. For classification we can use Fuzzy-c-mean clustering. It will analyse the mixed areas.

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