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REVIEW OF REMOTE SENSING IMAGE SEGMENTATION TECHNIQUES

Harmanpreet Kaur
Department of Electronics and Communication
Amritsar College of Engineering & Technology

Abstract

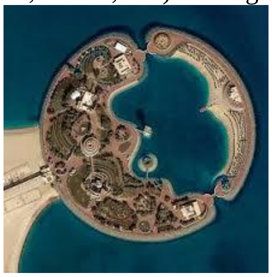
Image segmentation is an important tool in image processing and can serve as an efficient front end to sophisticated algorithms and thereby simplify subsequent processing. Image segmentation by region merging follows a particular order in the choice of regions. The target of segmentation is always to simplify and/or change the representation of a graphic into something that is more meaningful and simpler to analyze. Image segmentation is normally used to locate objects and boundaries (lines, curves, etc.) in images. To improve segmentation accuracy and the correctness, this paper proposed a Dynamic Statistical Region Merging (DSRM) algorithm to find the automatically select scale value. The purpose of this paper is to gather various segmentation techniques that can be used for the segmentation of remote sensing images (RSI). The paper provides good starting for researchers to find automatically select scale value using the combination of DSRM and fuzzy logic.

Keywords

Image segmentation, Multi-scale segmentation, Remote sensing image segmentation, Dynamic statistical region merging, Region growing.

1. Introduction

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The target of segmentation is always to simplify and/or change the representation of a graphic into something that is more meaningful and simpler to analyze. Image segmentation is normally used to locate objects and boundaries (lines, curves, etc.) in images.



Result of image segmentation is a couple of segments that collectively cover the entire image, or even a set of contours extracted from the image. All the pixels in a region are similar regarding some characteristic or computed property, such as color, intensity, or texture. Its performance directly determines the final consequence of some type of computer visual task. Up to now, you will find over one thousand types of segmentation approaches, which may be broadly classified as the Global-based (GB) and the Local-based (LB). The classical ways of the GB include Normalized-Cut, Efficient Graph-Based Method, Ratio-Cut, and Mean-shift and so on. The Watershed, Fractal Net Evolution Approach (FNEA), Statistical Region Merging (SRM), etc. are the LB methods. Recently, more and more attention has been paid on multi-scale segmentation. The multi-scale segmentation is applied widely on information extraction from RSI, e.g. change detection, classification and so on. Segmentation criteria can be arbitrarily complex and may consider global along with local criteria. A common requirement is that all regions must be connected in some sense. Multi-Scale segmentation is of two types: - (1) One-dimensional hierarchical signal segmentation. (2) Image segmentation and primal sketch. Various techniques have already been proposed for image segmentation. They are categorized in line with the application, imaging modality, and other factors. The segmentation techniques are (1) Thresholding approaches (2) Region growing approaches (3) Classification-based approaches (4) Artificial neural networks. The Statistical region merging **(**SRM**)** is an algorithm used for image segmentation. The algorithm can be used to judge the values within a regional span and grouped together based on the merging criteria resulting a smaller list. Some useful examples could be creating a group of generations within a population or in image processing grouping a group of neighboring pixels based on their shades that fall within a particular threshold. Using the Statistical Region Merging (SRM) for remote sensing image segmentation, the result is unsatisfactory. To improve the segmentation accuracy and the

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correctness Dynamic Statistical Region Merging (DSRM) is introduced. It tries to let probably the most similar regions to be tested first. Initially, it redefines the dissimilarity based-on regions. Then, it dynamically updates the dissimilarity and adjusts the test order during the task of merging. The accuracy of the DSRM is higher than the SRM and its computational complexity is approximately linear. Furthermore, we extend the DSRM to multi-band remote sensing image and utilize it for multi-scale segmentation. The SRM may also be used for multi-scale segmentation by construct a hierarchical structure. However, the SRM has some problems on the order followed to test the merging of regions. It only uses gray difference of adjacent pixels to define the Dissimilarity, based on that your testing order is decided. The order is determined in the beginning, and doesn't change during the task of region merging. This static testing order could cause incorrect merging in a few cases. Such as on blurry edge and gradual change region, the pixel difference (i.e. Dissimilarity) is also very small. So it could be tested before some object inner pixels. Moreover, if in addition, it satisfies the merging predicate, an incorrect merging occurs. With regions growing, one object is easily merged with another over blurry edge or gradual change region, causing under-segmentation. To lessen this incorrect merging, an energetic strategy is proposed. The Dynamic Statistical Region Merging (DSRM) tries to test the most similar regions first. Initially, the Dissimilarity is redefined as the difference of the regions, to which each pixel belongs. Then, it dynamically updates the dissimilarity and adjusts the test order during the task of merging. Therefore the blurry edge and the gradual change region can barely cause incorrectly merging.

2. Literature Survey

Jian Yang and et al. [2] proposed an unsupervised multi-band approach for scale parameter selection in the multi-scale image segmentation process, which uses spectral angle to measure the spectral homogeneity of segments. With the increasing scale parameter, spectral homogeneity of segments decreases until they match the objects in the real world. The index of spectral homogeneity has been used to determine multiple appropriate scale parameters. The performance of the proposed method was compared to a single-band based method through qualitative visual interpretation and quantitative discrepancy measures. Both methods are applied for segmenting two images: a Quick Bird scene of an urban area within Beijing, China and a Woldview-2 scene of a suburban area in Kashiwa, Japan. The proposed multi-band based segmentation scale parameter selection method outperforms the single-band based method with the better recognition for diverse land cov.er objects in different urban landscapes.

Jing Liu, Peijun Li and et al. [3] proposed a novel image segmentation method for VHR multispectral images using combined spectral and morphological information. The method can be summarized as follows. First, a morphological derivative profile has been calculated from an original multispectral image and combined with the spectral bands to quantify spectral-morphological characteristics of a pixel, which are considered as a criterion of homogeneity of neighboring pixels. Image segmentation was conducted using a seeded region-growing procedure, which has been based on the seed points automatically generated from the gradient image and dynamically added and the similarity between a seed pixel and its neighboring pixels in terms of spectral-morphological characteristics. The obtained segmentation result was further refined by a region merging procedure to generate a final segmentation result. The proposed method has been evaluated using three VHR images of urban and suburban areas and compared with two existing segmentation methods, in terms of visual inspection, quantitative evaluation and indirect evaluation. Experimental results demonstrate that the joint use of spectral and morphological information outperformed the use of morphological information alone. Furthermore, the proposed image segmentation method performed better than existing methods. The proposed image segmentation method was well applicable to the segmentation of VHR imagery over urban and suburban areas.

Zhijian Huang and et al. [4] has proposed the novel feature for remote sensing image analysis, called multi-scale relative salience (MsRS) feature. It was constructed by modeling the process of feature value changing with scales. Firstly, the multi-scale observation values at each site are obtained by convolved with recursive Gaussian filters for efficiency. Secondly, the multi-scale observation values are compared with the initial value to generate the relative salience. Lastly, the relative salience between multi-scales are embed into a single feature called the MsRS. The scale in MsRS has explicit spatial meaning which was convenient to choose appropriate scale for specified object. In the MsRS map, the inner of each object become more consistent, while the contrast between object and background has been enlarged. The MsRS can be used as preprocessing step of many applications, such as segmentation. Two state-of-art segmentations (the

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mean shift and the statistical region merging) are taken into experiments and the results proved that it brings improvement obviously.

Zhongwu Wang and et al. [8] introduced a new automatic Region-based Image Segmentation Algorithm based on k-means clustering (RISA), specifically designed for remote sensing applications. The algorithm includes five steps: k-means clustering, segment initialization, seed generation, region growing, and region merging. RISA was evaluated using a case study focusing on land-cover classification for two sites: an agricultural area in the Republic of South Africa and a residential area in Fresno, CA. High spatial resolution SPOT 5 and Quick Bird satellite imagery were used in the case study. RISA generated highly homogeneous regions based on visual inspection. The land-cover classification using the RISA-derived image segments resulted in higher accuracy than the classifications using the image segments derived from the Definiens software (eCognition) and original image pixels in combination with a minimum-distance classifier. Quantitative segmentation quality assessment using two object metrics showed RISA-derived segments successfully represented the reference objects.

Xueliang Zhang and et al. [11] proposed a Boundary-Constrained Multi-Scale Segmentation (BCMS) method. Firstly, adjacent pixels are aggregated to generate initial segmentation according to the local best region growing strategy. Then, the Region Adjacency Graph (RAG) was built based on initial segmentation. Finally, the local mutual best region merging strategy has been applied on RAG to produce multi-scale segmentation results. During the region merging process, a Step-Wise Scale Parameter (SWSP) strategy has been proposed to produce boundary-constrained multi-scale segmentation results. Moreover, in order to improve the accuracy of object boundaries, the property of edge strength was introduced as a merging criterion. A set of high spatial resolution remote sensing images was used in the experiment, e.g., Quick Bird, Worldview, and aerial image, to evaluate the effectiveness of the proposed method. The segmentation results of BCMS were compared with those of the commercial image analysis software eCognition. The experiment shows that BCMS can produce nested multi-scale segmentations with accurate and smooth boundaries, which proves the robustness of the proposed method.

Xueliang Zhang and et al. **[13]** proposed a hybrid region merging (HRM) method to segment high-resolution remote sensing images. HRM integrates the advantages of global-oriented and local-oriented region merging strategies into a unified framework. The globally most-similar pair of regions was used to determine the starting point of a growing region, which provides an elegant way to avoid the problem of starting point assignment and to enhance the optimization ability for local-oriented region merging. During the region growing procedure, the merging iterations are constrained within the local vicinity, so that the segmentation was accelerated and can reflect the local context, as compared with the global-oriented method. A set of high-resolution remote sensing images has been used to test the effectiveness of the HRM method, and three region-based remote sensing image segmentation methods were adopted for comparison, including the hierarchical stepwise optimization (HSWO) method, the local-mutual best region merging (LMM) method, and the multi resolution segmentation (MRS) method embedded in eCognition Developer software. Both the supervised evaluation and visual assessment show that HRM performs better than HSWO and LMM by combining both their advantages. The segmentation results of HRM and MRS were visually comparable, but HRM can describe objects as single regions better than MRS, and the supervised and unsupervised evaluation results further prove the superiority of HRM.

Jianyu Chen and et al. [15] proposed a new approach to multi scale segmentation of satellite multispectral imagery using edge information. The Canny edge detector was applied to perform multispectral edge detection. The detected edge features were then utilized in a multi scale segmentation loop, and the merge procedure for adjacent image objects has been controlled by a separability criterion that combines edge information with segmentation scale. The significance of the edge was measured by adjacent partitioned regions to perform edge assessment. The present method has based on a half-partition structure, which was composed of three steps: single edge detection, separated pixel grouping, and significant feature calculation. The spectral distance of the half-partitions separated by the edge was calculated, compared, and integrated into the edge information. The results show that the proposed approach works well on satellite multispectral images of a coastal area.

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3. Techniques Used

3.1 Region Splitting and Merging

The split-and-merge algorithm is composed by two steps. First, the method subdivides the entire image into smaller regions following a dissimilarity criterion. To divide the image, different strategies can be adopted such as a quad tree partition (where each region is subdivided into four equal regions) and a binary space partition (BSP) (where an optimal partition is selected to divide the region). Second, the neighbor regions obtained from the splitting step are merged if they verify a similarity criterion. These similarity and dissimilarity criteria can be based on an intensity range, gradient, contrast, region statistics, or texture. The combination of splitting and merging steps allows for the segmentation of arbitrary shapes, which are not constrained to vertical or horizontal lines, as occurs if only the splitting step is considered. Region splitting and merging subdivide an image initially into a set of arbitrary, disjoint regions and then merge and/or split the regions in an attempt to satisfy the necessary conditions.

3.2 K-Means Clustering

K-means is one of many simplest unsupervised learning algorithms that classify a given data set into certain quantity of clusters (assume k clusters) fixed a priori. The key idea is always to define k centroids, one for each single cluster. These centroids must certainly be put right into a cunning way, because different location causes different result. So, the greater choice is to position them as much as possible far from each other. The next thing is always to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early on grouping is done. Again re-calculate k new centroids of the clusters (resulting from the final step). After having these k new centroids, a fresh binding needs to be performed between the same data set points and the nearest new centroid. Repeat the strategy until centroids don't move any more. In the successive loops, the k centroids change their location detail by detail. The K-mean algorithm uses the following distance formula to compute the distance of the n data points from their respective j^{th} cluster center.

3.3 Thresholding

A thresholding procedure attempts to find out an intensity value, called the threshold, which separates the specified classes. The segmentation is then achieved by grouping all pixels with intensity greater compared to the threshold as you class and all other pixels as another class. Thresholding is a simple yet often effective means for obtaining segmentation in images. The limitation of thresholding is that, in its simplest form only two classes are generated and it cannot be applied to multi-channel images. Furthermore, thresholding doesn't take into account the spatial characteristics of a picture and therefore, are sensitive to noise. The key of this method is to select the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and k-means clustering. New methods suggested the usage of multi-dimensional fuzzy rule-based non-linear thresholds. In these works decision over each pixel's membership to a segment is based on multi-dimensional rules derived from fuzzy logic and evolutionary algorithms based on image lighting environment and application.

3.4 Region Growing

It can be classified as a pixel-based image segmentation method as it involves the choice of initial seed points. This method starts with initial “seed points” and then examines neighboring pixels (using either 4-connectivity or 8-connectivity) to find out perhaps the pixel neighbors ought to be added with the region. The method is iterated on, in the exact same manner as general data clustering algorithms. The region growing algorithm is described as:

(i) Select several seed points. Seed point selection is dependant on some user criterion (for example, pixels in a particular gray-level range, pixels evenly spaced on a grid, etc.). The first region begins as the complete precise location of the seeds.

(ii) The regions are then grown from these seed points to adjacent points according to a location membership criterion.

The criterion could be pixel intensity, gray level texture or color. Due to the fact the regions are grown on the building blocks of the criterion, the image information itself is important. For instance, if the criterion were pixel intensity, examine the adjacent pixels of seed points. If they've the same intensity value with the seed points, classify them to the seed points. It is surely an iterated process until there's no change in two successive iterative stages. The suitable choice of seed points is just a significant issue.

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3.5 Fuzzy C- Means Algorithm

In fuzzy clustering (also referred to as soft clustering), data elements can belong to more than one cluster, and associated with each element is a set of membership levels. These indicate the strength of the association between that data element and a particular cluster. Fuzzy clustering is a process of assigning these membership levels, and then using them to assign data elements to one or more clusters. One of the most widely used fuzzy clustering algorithms is the Fuzzy C-Means (FCM) Algorithm. The FCM algorithm attempts to partition a finite collection of N elements into a collection of c fuzzy clusters with respect to some given criterion. Given a finite set of data, the algorithm returns a list of C cluster centres and a partition matrix W.

In fuzzy clustering, every point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely to just one cluster. Thus, points on the edge of a cluster may be in the cluster to a lesser degree than points in the center of cluster. The algorithm minimizes intra-cluster variance as well, but has the same problems as k-means; the minimum is a local minimum, and the results depend on the initial choice of weights. Using a mixture of Gaussians along with the expectation-maximization algorithm is a more statistically formalized method which includes some of these ideas: partial membership in classes. Fuzzy c-means has been a very important tool for image processing in clustering objects in an image

3.6 Artificial Neural Networks

ANNs represent a paradigm for machine learning and can be utilized in a variety of ways for image segmentation. The most widely applied use in satellite imaging is as a classifier, where the weights are determined using training data, and the ANN is then used to segment new data. ANNs can be utilized in an unsupervised fashion as a clustering method, as well as for deformable models. Due to the many interconnections utilized in a neural network, spatial information can easily be incorporated into its classification procedures. Although ANNs are inherently parallel, their processing is normally simulated on a standard serial computer, thus reducing this potential computational advantage.

3.7 Dynamic Statistical Region Merging

Statistical region merging **(**SRM**)** is an algorithm used for image segmentation. The algorithm can be used to judge the values within a regional span and grouped together based on the merging criteria resulting a smaller list. Using the Statistical Region Merging (SRM) for remote sensing image segmentation, the result is unsatisfactory. To improve the segmentation accuracy and the correctness Dynamic Statistical Region Merging (DSRM) is introduced. It tries to let probably the most similar regions to be tested first. Initially, it redefines the dissimilarity based-on regions. Then, it dynamically updates the dissimilarity and adjusts the test order during the task of merging. The accuracy of the DSRM is higher than the SRM and its computational complexity is approximately linear.

4. Comparison Table

The table below shows a comparison of various liver segmentation techniques along with its features and limitations:

Ref. No	Authors	Year	Technique Used	Features	Limitations
[8]	Zhongwu Wang, John R. Jensen, Jungho Im	2010	Region- based Image segmentation Algorithm (RISA) based on k-means clustering	Higher accuracy than the Definiens software (eCognition)	Manual selection of scale leads to error in results
[16]	Calderero, Marques	2010	Unsupervised region merging technique	Complete and exhaustive evaluation was performed using different databases	Use of fuzzy logic is ignored

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[14]	Maire, M. ;Fowlkes, C. ; Malik, J.	2011	Contour detection and hierarchical image segmentation	Reduce the problem of image segmentation, computation at multiple image resolutions provide means of coupling.	Manual selection of scale leads to error in results
[6]	Xiang-Yang Wang, Xian-Jin Zhang and et al.	2012	Support vector machine (SVM) and fuzzy c- means	Effective computational behavior and effectiveness, decreases the time and increases the quality of color image segmentation.	Use of fuzzy logic is ignored
[15]	Jianyu Chen, Delu Pan, Qiankun Zhu and et al	2012	Edge-guided Multi-scale segmentation of satellite Multispectral Imagery.	It works well on satellite multispectral images of a coastal area.	Accuracy is low
[7]	Jorge E. Patino, Juan C. Duque	2013	Spectral mixture analysis, object-oriented classifications, and image texture measures.	Satellite remote sensing images has medium, high or very high spatial resolutions.	Computational time is high
[11]	Xueliang Zhang, Pengfeng Xiao, Xiaoqun Song, Jiangfeng She	2013	Boundary-Constrained Multi-Scale segmentation (BCMS), Step-Wise scale parameter (SWSP).	It produce accurate and smooth boundaries with robustness.	Can be used only for low contrast images
[12]	Stelios K. Mylonas, Dimitris G. Stavrakoudis, John B. Theocharis	2013	Genetic Sequential image segmentation (GeneSIS) algorithm.	It provides coverage, consistency and smoothness.	Poor quality of color image segmentation
[26]	Zhijian Huang, Jinfang Zhang, Xiang Li, Hui Zhang	2014	Statistical Region Merging Algorithm (SRM), Dynamic Statistical Region Merging Algorithm (DSRM).	Accuracy of DSRM is higher than SRM and its computational complexity is approximately linear.	Manual selection of scale leads to error in results
[4]	Zhijian Huang, Jinfang Zhang, Fanjiang Xu	2014	Novel Multi-scale relative salience (MsRs) feature	Inner of each object become more consistent while contrast between object and background has enlarged. It brings improvement.	Use of fuzzy logic is ignored, low accuracy.

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[5]	Chao Wang, Ai-Ye Shi, Xin Wang and et al	2014	Wavelet transform and improved JSEG algorithm (WJSEG).	Effectiveness and Reliability.	Requires high computational time
[10]	Saman Ghaffarian, Salar Ghaffarian	2014	Automatic histogram-based fuzzy C- means (AHFCM) algorithm.	Efficient Segmentation and robustness.	Less effective and non-reliable.
[9]	Jianqiang Gao, Lizhong Xu	2015	Fisher linear discriminant analysis (FLDA).	Projection matrix (PM) can be obtained by using within-class and between-class sets.	Use of fuzzy logic is ignored, low accuracy.
[3]	Jing Liu, Peijun Li , Xue Wang,	2015	Combined Spectral and morphological information.	Well applicable to the segmentation of VHR imagery over urban and suburban areas.	Non- reliable and slow method.

5. Conclusion and Future Scope

In this paper, a survey on various image segmentation techniques has been done. It has been concluded that the segmentation performance relates closely to the scale but the scale is selected manually in majority of the existing research. Also, the use of fuzzy logic to find automatic scale value is not used in the existing research. Therefore, in future an algorithm is designed using a combination of fuzzy logic and dynamic statistical region merging (DSRM) in order to automatically select scale value.

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