Satellite image Segmentation using Wavelets

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Abstract:

Model-based image segmentation plays an important role in image analysis and retrival,it performs much more efficient then other non-parametric methods.Satellite images are useful for the identification of distribution of lakes,rivers,soil,vegetations,etc.segmentationn is done automatically by using by discrete wavelets,which is faster in computation and efficient than other methods of segmentation. In this we first perform DWT, then find initial parameters like mean, variance, shaping parameter by using histogram based methods and final parametrs by using EM and finally segment the image using ML estimation.In this we obtain segmented images of much more superoior quality compared to other segmentation methods

Keywords: Discrete wavelets, Satellite images, EM algorithm, ML estimation, Histogram

Introduction

Image segmentation is an important task in image analysis in which image pixels of same features are grouped together into homogenous regions.. Image segmentation is a process of extracting and representing information from an image in order to group pixels together into regions of similarity. Image segmentation is classified into three categories viz., i) *Manual* i.e.,supervised or interactive in which the pixels belonging to the same intensity range pointed out manually and segmented, the disadvantage is that it consumes more time if the image is large. ii) *Automatic* i.e., unsupervised which is more complex and algorithms need some priori information such as probability of the objects .Having a special distribution to carry out the segmentation.iii) *Semi-Automatic* is the combination of manual and automatic segmentation.

The pixel intensity based image segmentation is obtained using Histogram-Based method, Edge-Based method, Region-Based Method and Model-Based method. Model-Based segmentation algorithms are more efficientCompared to other methods as they are dependent on suitable probability distribution attributed to the pixel intensities in the entire image. To achieve close approximation to the realistic situations, the pixel intensities in each region follow Generalized Gaussian Distribution (GGD). Some of the practical applications of image segmentation are Medical Imaging to locate tumours and other pathologies, locate objects in satellite images viz., roads, forests, etc., automated-recognition system to inspect the electronic assemblies, biometrics, automatic traffic controlling systems, machine vision, separate and track regions appearing in consequent frames of an image sequence and real time mobile robot applications employing vision systems.

***Motivation**:* Avaliability of satellite images when used operaitonally considering bad weather conditions or impairments.It may be thus necessary to use images from any sensor available and also the objects in image are smaller. Model based algorithms are used for efficient segmentation of images where intensity is the prime feature. The problem of random initialization is overcome by using Histogram based estimation. The Wavelet transform solves the problem of resolution which can indicate the signal without information loss and reduces the complexity. The segmentation is faster since approximation band coefficients of DWT are considered.

***Contribution**:* In this paper we perform segmentation on satellite images and obtain images with more resolution.First we approximate image as bands which contain significant information.

The initial parameters and final parameters are obtained by applying Histogram based algorithm and Expectation and Maximization algorithm respectively. GGD model is constructed and segmented by Maximum Likelihood estimation of each approximation coefficient.

Related Work

1. Bayesian[1] unsupervised satellite image segmentation, using contextual methods. It is shown, via a simulation study, that the spatial or spectral context contribution is sensitive to image parameters such as homogeneity, means, variances, and spatial or spectral correlations of the noise. From this one may choose the best context contribution according to the estimated values of the above parameters. The parameter estimation is done by SEM, a densities mixture estimator which is a stochastic variant of the EM (expectation-maximization) algorithm. Another simulation study shows good robustness of the SEM algorithm with respect to different image parameters. Thus, modification of the behaviour of the contextual methods, when the SEM-based unsupervised approaches are considered, is limited, and the conclusions of the supervised simulation study stay valid. An adaptive unsupervised method using more relevant contextual features is proposed. Different SEM-based unsupervised contextual segmentation methods, applied to two real SPOT images, give consistently better results than a classical histogram-based method.

2).Watershed is one of the classic regions in the field of topography. A drop of the water falling it Flows down until it reaches the button of the region. In the field of image processing, gray scale Pictures are often considered as topographic reliefs, the numerical value (DN) of each pixel is given Corresponding to the elevation[2] at this point (Vincent, Soille, 1991).This idea says if we have a minima point, by falling water, region and the boundary can be achieved. Watershed use image gradient to initial point and region can obtain by region growing.

3). A Multispectral satellite image is addressed. An integration of rough-set-theoretic[3] knowledge extraction, the Expectation Maximization (EM) algorithm, and minimal spanning tree (MST) clustering is described. EM provides the statistical model of the data and handles the associated measurement and representation uncertainties. Rough-set theory helps in faster convergence and in avoiding the local minima problem, thereby enhancing the performance of EM. For rough-set-theoretic rule generation, each band is discredited using fuzzy-correlation-based gray-level thresholding. MST enables determination of non convex clusters. Since this is applied on Gaussians, determined by granules, rather than on the original data points, time required is very low. These features are demonstrated on two IRS-1A four-band images. Comparison with related methods is made in terms of computation time and a cluster quality measure.

4). Estimation of fuzzy Gaussian distribution mixture with applications to unsupervised statistical fuzzy image segmentation. In a general way, the fuzzy approach enriches the current statistical models by adding a fuzzy class, which has several interpretations in signal processing. One such interpretation in image segmentation is the simultaneous appearance of several thematic classes on the same site. We introduce a new procedure for estimating of fuzzy mixtures, which is an adaptation of the iterative conditional estimation (ICE) algorithm[4] to the fuzzy framework, We first describe the blind estimation, i.e., without taking into account any spatial information, valid in any context of independent noisy observations. Then we introduce, in a manner analogous to classical hard segmentation, the spatial information by two different approaches: contextual segmentation and adaptive blind segmentation.[6] In the first case, the spatial information is taken into account at the segmentation step level, and in the second case it is taken into account at the parameter estimation step level. The results obtained with the iterative conditional estimation algorithm are compared to those obtained with expectation-maximization (EM) and the stochastic EM algorithms, on both parameter estimation and unsupervised segmentation levels, via simulations. The methods proposed appear as complementary to the fuzzy C-means algorithms.

[5] Sharon et al., [7] introduced fast multi-scale algorithm which uses a process of recursive weighted aggregation to detect the distinctive segments at different scales. It

determines an approximate solution to normalized cuts in time domain i.e., linear in the size of image with few operations per pixel. The disadvantage is that the segmented image fails to give smoother boundaries

Model: In this section discuss definitions of various parameters.

1).Mean: The average intensity of a region is defined as the *mean* of pixel intensities in that region. The mean μ_z of the intensities over N pixels with in a region is given by

$$\mu_z = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad \text{.......... (1)}$$

Alternatively, we can use normalized intensity histogram p(z_i) where i=0,1,2,…….,L-1 and L is the number of possible intensity values is given as

$$\mu = \sum_{i=1}^{L} z_i \; p(z_i) \qquad \text{………. (2)}$$

2). variance: The *variance* of the intensities within a region K with N pixels is given as

$$\sigma_z^2 = \frac{1}{N}\sum_{i=0}^{N}(x_i - \mu_z)^2 \qquad \text{……… (3)}$$

Using histogram formulation the *variance* is given as

$$\sigma^2 = \sum_{i=0}^{L}(z_i - \mu)^2 \; p(z_i) \qquad \text{……… (4)}$$

3). *Probability Distribution Function (PDF) of the intensities*: The PDF p(z), is the probability that an intensity chosen from the region is less than or equal to a given intensity value z.As z increases from -∞ to +∞,p(z) increases from 0 to1.p(z) is monotonic,non-decreasinf in z and thus$\frac{dp}{dz} \geq$ 0.

4).Shaping parameter p: It defines the peakness of the distribution which varies from 1 to∞.The GGD becomes laplacian Distribution if p=1, Gaussian distribution if p=2 and Uniform Distribution if p$\rightarrow \infty$.

5).Computational time: Time required for the execution of the algorithm.

Algorithm

Input: Image of variable size

Output: Segmented regions.

1. Discrete wavelet transform is applied on image and approximation band is considered.

2. Histogram based method is applied to obtain parameters like mean, variance and mixing parameter.

3. Shaping parameter P is determined.

4. Expectation and Maximization algorithm is used to get update final parameters.

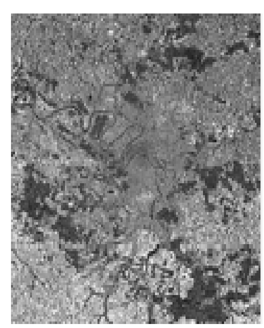
5. PDF of Generalized Gaussian Distribution is determined.

6. Segmentation is obtained using Maximum-Likelihood estimation.

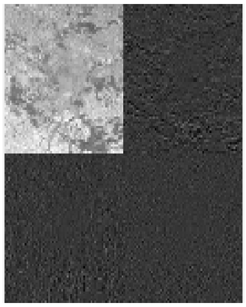
Results

Segmentation is applied for various satellite images of jpeg format files and their results are shown below. Here the number of segments are two that is k=2, foreground and background can be differentiated in an image.

Original Image



Gray Image

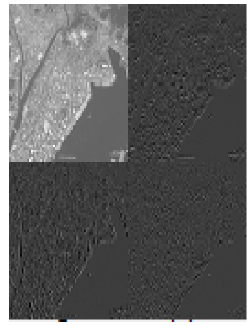


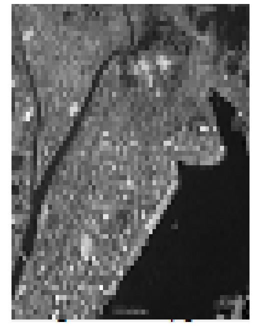
Transformed Image
Approximation Image

Segmented1 Segmented2

Fig 1

Original Image Gray Image





Transformed Image Approximation Image

Segmented1 Segmented2

Fig2

Conclusion

In this paper we proposed segmentation on satellite images. By this we assign a label to each pixel such that pixels which share same labels will have similar visual characteristics. Satellite images in which pixels in adjacent regions are significantly different with same properties, can be easily segmented with the help of algorithm mentioned above .Even though image segmentation of satellite images is time consuming process, with the help of our algorithm we can do it fastly ,efficiently and effectively performs on larger images and performs much superior to other image segmentation methods.

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