Segmentation of Multispectral Remote-sensing Images based on Markov Random Fields

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Abstract -- An unsupervised approach for texture segmentation of multispectral remote-sensing images based on Gaussian Markov random fields (GMRFs) is proposed. At first, we treat the false-color information of Spot satellite images as *RGB* attributes and then transform them to *HSI* attributes. Secondly, a scale-space filter is used to threshold the hue histogram to quantize the color set which represents the principal color components in the original image. Thirdly, the global GMRF parameters are estimated from the original image for global segmentation. Fourthly, we label each pixel of the image based on the quantized color set and the GMRF parameters to maximize a posterior color distribution probability to achieve the global segmentation. Fifthly, a criterion is used to judge whether every pixel in the global-segmented image is within a local textured region or not. Finally, the pixels in a local textured region are further estimated the local GMRF parameters and clustered based on the parameters. Seven Spot images were segmented to demonstrate the ability of the proposed approach. Moreover, the scale-space filter, the MRF-based global segmentation, and the pure local (texture) parameter classification are sequentially evaluated their performance.

1. INTRODUCTION

The purely intensity-based segmentation methods only use spectral information for image segmentation, then textured regions cannot be correctly segmented. To exactly segment multispectral remote-sensing images, spatial information should be considered to combine with spectral information. It means that neighborhood-based methods should be employed for textured multispectral-image segmentation.

The neighborhood-based approaches which use Markov random fields (MRFs) consider both spectral and spatial information [2, 6, 9, 10]. The utilization of both kinds of information can classify image region more exact than the intensity-based methods which only use spectral information. Many methods which supervise maximum a posterior probability (MAP) segmentation using MRFs are based on the methodology introduced by Geman and Geman [4]. The Hammersley-Clifford theorem [4, 5] established the equivalence between the conditional probabilities of the local characteristics in MRFs and the local energy potential in Gibbs distribution. The model parameters are assumed a priori known in supervised image segmentation; however, many researchers have addressed the difficult problem of unsupervised segmentation for which no priori knowledge of texture parameters is assumed. Most of the unsupervised segmentation methods assume an image model previously and estimate model parameters before clustering [3, 7].

In this paper, an unsupervised approach for texture segmentation of multispectral remote-sensing images based on MRFs is proposed. We assume that color of each pixel is under the influence of the colors of its neighboring pixels and an additive noise. The noise are assumed to form a Gaussian distribution. A Gaussian Markov random field (GMRF) is a special case of MRFs and we use a GMRF to model the multispectral remote-sensing images and then segment the images [1, 8].

2. SEGMENTATION

The proposed system is an unsupervised algorithm for segmenting the homogeneous textured regions in multispectral remote-sensing images without the prior information, such as the number of texture regions, texture parameters, and the color distribution. To achieve the goal, many processes are adopted here.

At first, we take the three spectra of a multispectral *SPOT* image as *RGB* components to compose the false-color image and transform *RGB* color space to *HSI* color space.

Secondly, we detect how many and what major types of colors compose the original image. There are several optimal approaches can achieve this goal; for example, k-means clustering, maximin clustering, and histogram thresholding. A number of clustering approaches need to know the number of clusters and spend much more time than the histogram-based approaches, so we adopt histogram thresholding method based on the scale-space filter to quantize the hue values. From this step, a few pixels at region contours may be mislabeled; however, we can know the major types of color which compose the image and call these quantized color values as *color set*.

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Thirdly, we use the least-squares method to estimate the global GMRF parameters to be included in a posterior color distribution for the global segmentation of the image.

Fourthly, we label each pixel of the image using *RGB* values based on the quantized *color set* and the GMRF parameters to maximize a posterior distribution probability (MAP) to reduce the cases of mislabeling at region contours. The global parameters used in this step are estimated from the statistical result of the whole image. The results of labeling provide more smooth region contours than the results of thresholding on *hue* histogram. In fact, the goal of this step is to separate the regions which is homogenous in color and it will provide more simplified texture distribution of the original image to benefit the local (texture) parameter estimation in the next step. The results of this step are called the *global-segmented* (*labeled*) *image*.

Fifthly, the pixels are classified into two classes based on their local random property. Pixels possessing higher randomness will be further processed with a local spatial information. We estimate local parameters for these pixels. In fact, the result of parameter classification for each pixel sometimes offers coarse boundaries around some regions which we don't think they are textured regions but regions homogeneous in color. This is the critical problem in local parameter classification. The parameter estimation occupies a large proportion of the whole computation time; therefore, we reserve partial results of the global-segmented image based on global parameters and estimate local parameters of remainder pixels for classification. A criterion is proposed to decide whether a pixel should be estimated local parameters or not. For the pixels should be estimated local parameters, we use a fixed-size window which centered at each one of them and estimate the local parameters from the statistical results of the range of the fixed-size window. The parameters we mention here represent the relationship between the central pixel and their neighboring pixels. However, to produce a better parameter vector to represent texture property of each pixel, the color mean and Gaussian noise variance of the window range are considered simultaneously.

Finally, we develop a criterion to classify the estimated local parameters of the higher-random pixels. The criterion takes the maximum of all component distances to represent the distance between two parameter vectors and classify these parameter vectors by the distances between each vector and each cluster center. Since the texture property of a pixel is represented by the local parameter vector, the homogeneous textured region can be separated after parameter classification [7].

3. EXPERIMENTS

Seven *SPOT* remote-sensing images were segmented by the proposed approach to demonstrate that the proposed approach is suitable for remote-sensing image segmentation. Moreover, the histogram thresholding based on the scale-space filter, the MRF-based global segmentation, and the pure local (texture) parameter classification are sequentially evaluated their performance.

One experimental result is shown here. An original 256×256 *SPOT* satellite image of SDS02 is shown in Fig.1(a), The result of histogram thresholding based on the scale-space filter, the MRF-based global segmentation result based on the previous thresholded result, the local texture segmentation result based on the previous two processed result, and the complete result without pixel classification are shown in Fig.1(b)~(e), respectively.

4. CONCLUSION

From the experimental results, we can draw several conclusions as follows:

(1) The proposed global segmentation can reduce the mislabeling problem in ssf-based histogram thresholding and simplify texture distribution for more effective local parameters estimation and classification.

(2) The MRF-based global segmentation is an unsupervised segmentation and can provide a better texture segmentation result than the local texture classification. Meanwhile, the proposed system spends less computation time to finish work for it selects partial specific pixels of the image for local parameters estimation and classification.

(3) The Manjuanth-Chellappa local segmentation [7] were partially implemented and applied to classify the estimated texture vectors; however, due to the special property of remote-sensing images, our proposed approach made much better results than the pure local texture segmentation.

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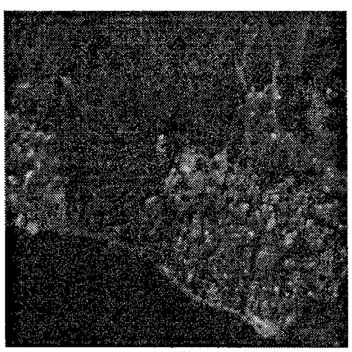
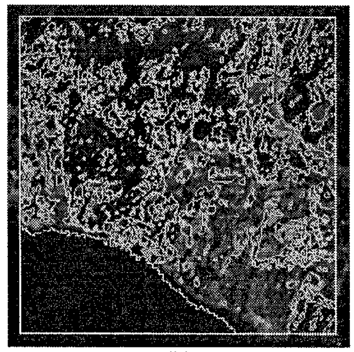
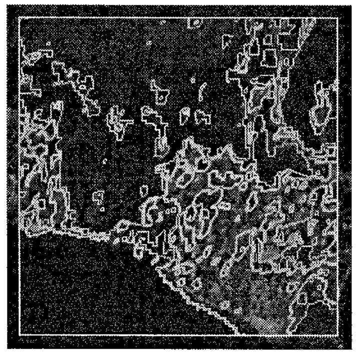


(a)

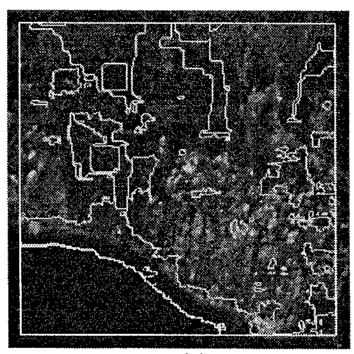


(b)



(c)

(d)



(e)

Fig. 1. Segment results of image SDS02. (a) The original image; (b) the ssf-based thresholded result; (c) the result after global segmentation; (d) the result after local segmentation; and (e) the local-segmented result without pixel classification.