Segmentation of high resolution remote sensing images by combining hidden Markov random field model and fuzzy c-means at the region level

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Abstract. In high spatial resolution remote-sensing images, complex landscapes are usually accompanied with macro texture patterns, which often adversely affect segmentation accuracy, mainly due to their high spatial and spectral heterogeneity. To address this problem, this study develops an image segmentation method by combining the iteration procedure of fuzzy c-means (FCM) clustering and hidden Markov random field (HMRF) model at the region level. The performance of the proposed method was assessed through aerial images. Results indicate that the proposed method can improve image segmentation accuracy, compared to FLICM, HMRF-FCM, MRR-MRF, and IRGS.

1. Introduction

Image segmentation is one of the most important steps in the interpretation of remote sensing images. It aims at partitioning an image into disjoint meaningfully homogeneous regions. In the past decades, many different image segmentation techniques have been proposed [1, 2, 3, 4]. Among them, those based on fuzzy c-means (FCM) [5] and Markov random field (MRF) models [6] are the most popular ones. Being able to retain more information from the original image, FCM has robust characteristics for ambiguity [7]. However, the standard FCM ignores the information about spatial context, which makes it very sensitive to noise, outliers, and other imaging artifacts. The MRF model provides a powerful and formal way to model the information about the mutual influences among image pixels. Nevertheless, it fails to consider image ambiguity because its estimation approach, such as expectation-maximization (EM), needs to regard pixel labels as known quantities [8, 9].

Motivated by the success of region-level MRF-based segmentation methods, which make it possible to capture and utilize correlations over different image regions, in this study, we propose an image segmentation method by combining the iteration procedure of FCM and HMRF at the region level.

2. The Proposed Image Segmentation Algorithm

2.1 Framework of the proposed algorithm

Fig. 1 shows the image segmentation framework of the proposed RFCMHMRF algorithm. First of all, a deliberate over-segmentation of the original high spatial resolution image is obtained. Then, attributes for each region, such as its area and boundary length, are calculated, and also a region adjacency graph (RAG) is built according to the relationships between neighboring regions: Each region corresponds to a node of the RAG, and the relationship between two different regions is defined by their adjacency as edges of the graph. Finally, segmentation result is obtained by using an iterative procedure between one-step FCM and one-step HMRF. The spatial relationships between neighboring regions, as well as their attributes, are integrated into the prior probability of HMRF and

the dissimilarity of FCM to capture and utilize the large range variations of macro texture patterns in the original image.
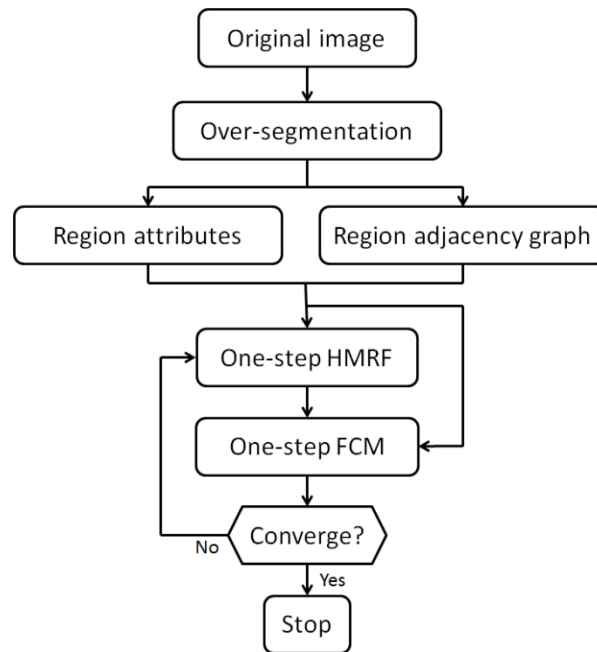

Fig. 1 The framework of the proposed method

2.2 The core of the algorithm

The main procedure of the proposed RFCMHMRF algorithm is as follows.

Step 1. Preparation: Set the number of different land-cover types K, the threshold of segmentation error ϵ, and the maximal iteration number T. Get a deliberate over-segmentation, and then compute the boundary length $b_{i,j}$ and pixel number n_i for each region.

Step 2. Initialization: In the first iteration ($t = 1$), derive the pixel-level fuzzy memberships by using the original FCM, and compute the initial region-level fuzzy memberships by $u_{i,k}^{(t)} = \sum_{s \in r_i} u_{s,k} / n_i$, then, establish the membership matrix $\{u_{i,k}^{(t)}\}$ and derive a segmentation $x^{(t)}$ by Equation (13).

Step 3. One-step HMRF: Derive the mean $\mu_k^{(t)}$ and covariance matrix $\Sigma_k^{(t)}$ for HMRF by Equation (11) and Equation (12), respectively. For each region, get the prior probability $P(x_{r_i} = k | \eta_{r_i})$ by Equation (3) and the conditional probability $P(y_{r_i} | x_{r_i})$ by Equation (5), and then generate the normalized joint probability matrix $\{z_{i,k}\}$ by Equation (7).

Step 4. One-step FCM: For each region, compute the dissimilarity function that is given by Equation (9), and then generate the distance matrix $\{d_{i,k}\}$. Generate the new region-level fuzzy membership function that is given by Equation (10), and obtain the new membership matrix $\{u_{i,k}^{(t+1)}\}$, which is to be used in the next iteration process.

Step 5. Convergence: Derive a new segmentation result $x^{(t+1)}$ according to Equation (13). In case of convergence (the rate of pixel labels changed between two successive iterations is smaller than ϵ or $t > T$), stop iteration, output x^t; otherwise, set $t = t + 1$, and go to Step 3.

3. Experimental results and discussions

In this section, to test the performance of the RFCMHMRF algorithm, we carry out experiments on aerial images. Apart from our algorithm, four competitive methods are used to compare the segmentation results:
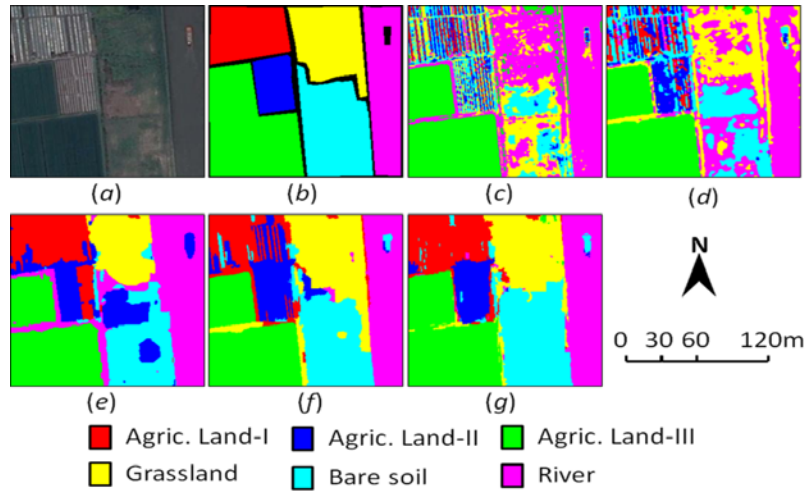

Fig. 2: Segmentation results of AER-SH. (a) AER-SH. (b) Ground truth. (c) Result of FLICM. (d) Result of HMRF-FCM. (e) Result of MRR-MRF. (f) Result of IRGS. (g) Result of RFCMHMRF.

FLICM [7]: It improves the traditional FCM by using fuzzy local (both spatial and spectral) similarity measure, aiming to guarantee noise insensitiveness and image detail preservation.

HMRF-FCM [8]: It combines fuzzy clustering and HMRF together to explore the spatial coherency modeling capabilities of MRF in the fuzzy clustering procedure.

MRR-MRF [11]: It uses the multiresolution region-based weighted average and difference to provide a good pixel-level descriptor for the large range variations of macro texture patterns.

IRGS [10]: It is a region-level MRF-based method, which uses region growing technique in searching for the solutions of the objective functions.

The overall accuracy o and the Kappa coefficient κ are used to measure the degree of similarity between segmentation results and the ground truth. Let c_{ij} be the proportion of pixels that were assigned to the ith land-cover type of the segmentation result and j^{th} land-cover type of the ground truth. Denote $c_{i\cdot} = \sum_{j=1}^{K} c_{ij}$ and $c_{\cdot j} = \sum_{i=1}^{K} P_{ij}$, then $o = \sum_{i=1}^{K} c_{ii}$ and $\kappa = \frac{\sum_{i=1}^{K} c_{ii} - \sum_{i=1}^{K} c_{i\cdot} c_{\cdot i}}{1 - \sum_{i=1}^{K} c_{i\cdot} c_{\cdot i}}$

Fig. 2(a), called AER-SH, is a piece of aerial image of an outskirt of Shanghai, China. Its size is 258×271 pixels. It includes grassland, bare soil, a river, and three types of agricultural land. Different types of macro texture patterns are distributed throughout the image. The deliberate over-segmentation is obtained by the meanshift algorithm [18] with the minimum area $a = 20$, the spatial bandwidth $\rho = 4$, and the range bandwidth $r = 4$.

Table 1: Comparison of segmentation results.

Method	AER-SH		SP5-PS	
	o	k	o	k
FLICM	0.5443	0.4358	0.6294	0.4408
HMRF-FCM	0.6909	0.619	0.6909	0.5334
MRR-MRF	0.8733	0.8298	0.8655	0.817
IRGS	0.8937	0.8698	0.8734	0.8069
RFCMHMRF	0.9524	0.9414	0.9086	0.8607

Table 1 shows the overall accuracy and Kappa coefficient of each algorithm on AER-SH. Both indicators of the proposed algorithm have the highest values, which prove that the proposed method can largely improve the results of this scenario.

4. Summary

To address the problems caused by macro texture patterns in high resolution remote sensing images, in this study, we develop the RFCMHMRF algorithm by combining the iterative procedure of HMRF and FCM at the region level. With the region-level spatial and structural information modeled by the fuzzy prior probability function of HMRF and the probabilistic dissimilarity function of FCM, the negative impact of macro texture patterns in some complex land-cover types is reduced. Experimental results show that RFCMHMRF can obtain more accurate segmentation results than FLICM, HMRF-FCM, MRR-MRF, and IRGS, when segmenting images with macro texture patterns.

Acknowledgements

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