A novel unsupervised segmentation for remote sensing image using MRF

Jiajing Wang[1, 2*], Shuhong Jiao[1], Zhenyu Sun[3]

[1]*Faculty of Information and Communication Engineering, Harbin Engineering University, No.145, Nan Tong Road Harbin, Heilongjiang, China*

[2]*No.92677 Unit of PLA, Dalian, Liaoning, China*

[3]*No.91550 Unit of PLA, Dalian, Liaoning, China*

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Abstract

The image segmentation is the basis of image interpretation in remote sensing applications and plays vital role in image analysis. The Markov Random Field (MRF) approach is widely studied for use in segmentation of remote sensing image, which is an important extraction technique in recognition problems. This paper presents an unsupervised segmentation method for remote sensing image using the MRF. A novel neighbourhood system for the energy function has been proposed, the segmentation of remote sensing image and the optimization process of the parameters are performed simultaneously for the unsupervised segmentation in iterative condition. The experimental results on Synthetic Aperture Radar (SAR) images show that the proposed method performs better than the conventional Bayesian segmentation methods.

Keywords: remote sensing image, MRF, unsupervised segmentation, parameter estimation, SAR

1 Introduction

The rapid development of satellite remote sensing technology has enabled the multi-level, multi-angle, stereoscopic, omni bearing, and all-weather observation of earth. The quality of the observation mainly depends on the interpretation of remote sensing image; therefore, research on the remote sensing image has been a hotspot nowadays [1]. However, segmentation play an important role in the remote sensing technology, it can provide the image structure information, and establish the foundation for automatic target recognition on remote sensing system, it is crucial for understanding and interpreting remote sensing image.

In this paper, a novel method for remote sensing image segmentation is presented, with specific application to Synthetic Aperture Radar (SAR). The SAR is an active remote sensing system that generates and transmits microwave electromagnetic (EM) radiation to the surface of a target region [2]. And the SAR imaging does not get influenced by the weather conditions, geographical location, time of the day, and it can find hidden underground target through the vegetation, therefore, it has been widely applied to military and civil sectors. However, the images of SAR are heavily corrupted by speckle noise due to constructive and destructive EM wave interference during image acquisition [3]. Speckle noise is modelled as a multiplicative noise and gives the images grainy appearance. It can affect automated image segmentation. The MRF model can well suppress the influence of the speckle on segmentation results, so it has been widely applied to the remote sensing image segmentation applications. Dong [4] used Gaussian Markov Random Field model to complete the segmentation of remote sensing image. Ludwin [5] detected oil spill in SAR images by MRF and image fusion. Recently, Liu et al. [6] presented Triplet Markov Field (TMF) to PolSAR image classification, and D. Elia et al. [7] presented tree structured Markov Random Fields for remote sensing image classification.

A new neighbourhood system of MRF has been developed and presented in this paper, and the image segmentation is performed using the optimized parameters, which acquired through the iterative process for the unsupervised segmentation applications. The rest of the paper is organized as follows: Section 2 introduces the two MRF models including the new neighbourhood system definition and the estimation process of the parameters; section 3 gives a detailed analysis of the unsupervised evaluation method; the results of experiments and comparisons are reported in Section 4; finally, section 5 presents a conclusion and future plans.

2 MRF models

Let $S=\{s=(i,j)\,|\,1\le i\le M, 1\le j\le N\}$ be the set of image sites which specify the location of the pixel, M and N are the width and height of the image respectively. $X=\{X_s, s\in S\}$ and $Y=\{Y_s, s\in S\}$ are two random fields defined in S. X is the hidden field where each X_s represents the class of the site s and takes its value from a

[*] ***Corresponding author*** e-mail: 1656975717@qq.com

finite set $\Psi = \{1, \cdots G\}$. Y is the observed field where each Y_s represents the observed data of site s and takes its value from the gray level value. Both of the two random fields need to be considered in building a uniform model of the whole image.

Assume θ_X and θ_Y are the relevant parameters of the field X and Y respectively, and they are distributed uniformly and independent of each other. For image segmentation of MRF model, the task is to recover the hidden field X from the observed field Y. When the observed field data Y are known, seek the estimation class $\hat{X}$ for maximum a posteriori probability, in other words, find the optimal solution $(\hat{X}, \hat{\theta}_X, \hat{\theta}_Y)$. The optimal solution belongs to a variable space $\Omega = (X, \theta_X, \theta_Y)$:

$$\begin{aligned} &\hat{X}_{MAP} = \arg\max_{\Omega} P(\Omega|Y) = \\ &\arg\max_{\Omega} \frac{P(Y,\Omega)}{P(Y)} = \arg\max_{\Omega} P(Y|\Omega)P(\Omega) = \\ &\arg\max_{(X,\theta_X,\theta_Y)} P(Y|X,\theta_X,\theta_Y)P(X|\theta_X,\theta_Y)P(\theta_X,\theta_Y) = \\ &\arg\max_{(X,\theta_X,\theta_Y)} P(Y|X,\theta_Y)P(X|\theta_X)P(\theta_X)P(\theta_Y) = \\ &= \arg\max_{(X,\theta_X,\theta_Y)} P(Y|X,\theta_Y)P(X|\theta_X). \end{aligned} \quad (1)$$

Hence, finding the optimal solution of the variable space turns into optimizing the Equation (1) under the condition of a given observed field. The models of hidden field X and observed field Y are built separately as follow.

2.1 MODEL OF OBSERVED FIELD

The observed field in the MRF model is based on the original remote sensing image. It can reflect the characteristics of the original image data and fully describe the change of texture details of remote sensing image. The Gaussian Markov Random Fields (GMRF) model is used to represent the conditional distribution of remote sensing image:

$$P(Y|X,\theta_Y) = \prod_{s\in S}\left[\frac{1}{\sigma_{x_s}^{1/2}(2\pi)^{d/2}}\exp\left\{-\frac{1}{2}(y_s-\mu_{x_s})^T\sigma_{x_s}^{-1}(y_s-\mu_{x_s})\right\}\right]^{1/d}, \quad (2)$$

where μ is the mean value, σ is the standard deviation, and d represents the number of y_s in observed blocks. $\theta_Y = \{\theta_Y^g; g \in (1, \cdots, G)\}$ indicates the relevant parameters of the observed field Y; $\theta_Y^g = \{\mu_g, \sigma_g\}$, $g \in \Psi$ and θ_Y can be obtained by Maximum likelihood (ML) [8] estimate:

$$\hat{\mu}_g = \frac{1}{n_g}\sum_{s\in S, x_s \in g} Y_s , \quad (3)$$

$$\hat{\sigma}_g = \frac{1}{n_g}\sum_{s\in S, x_s \in g} \left(Y_s - \hat{\mu}_g\right)\left(Y_s - \hat{\mu}_g\right)^T . \quad (4)$$

The ML estimate $\hat{\theta}_Y$ is obtained using Equations (3) and (4), it has a closed form, and it is iteratively updated with the segmentation calculation.

2.2 MODEL OF HIDDEN FIELD AND A NEW ENERGY SYSTEM

It has been proven by feasibility and rationality in a number of related studies that the hidden field X can be considered as the MRF. Considering the relationship between MRF and Gibbs, the probability distribution of the hidden field X can be described by the neighbourhood system and energy function. Using the MRF-Gibbs equivalence [9], the probability distribution can be directly written as:

$$P(X = x) = Z^{-1}\exp(-\sum_{c\in C} V_c(X)) , \quad (5)$$

where Z is a normalization constant, $V_c(X)$ is the potential energy function related to the group c and $U(X) = \sum_{c\in C} V_c(X)$ constitutes the energy function. C is the collection of all the groups. In this paper, the MLL model is used to describe the potential energy function as:

$$V(x_s, x_n) = \begin{cases} \beta_s & (x_s = x_n) \\ -\beta_s & (x_s \neq x_n) \end{cases}. \quad (6)$$

The classic 8 neighbourhood system with the information of location is developed in this study. As shown in Figure 1, x and y are the horizontal and vertical neighbourhoods of the site S , respectively. λ_x and λ_y are unit vectors of x and y . $\lambda_x = \pm 1, \lambda_y = 0$, for s and n are horizontal; $\lambda_x = 0, \lambda_y = \pm 1$, for s and n are vertical; and $\lambda_x = \pm 1, \lambda_y = \pm 1$, for s and n are diagonal.

According to [10] and the theorem of Gravity, the relative position of pixels is closer when the interaction is stronger. The Euclidean distance is used to define the energy parameter related to the group $c = (s, n)$:

$$\beta_s(s,n) = \frac{1}{d^2(s,n)[\frac{\lambda_x^2(s,n)}{\beta} + \frac{\lambda_y^2(s,n)}{\beta}]} , \quad (7)$$

where $d(s,n)=\sqrt{\lambda_x^2+\lambda_y^2}$. To achieve the unsupervised segmentation, the optimal values of estimated parameters need to be obtained.

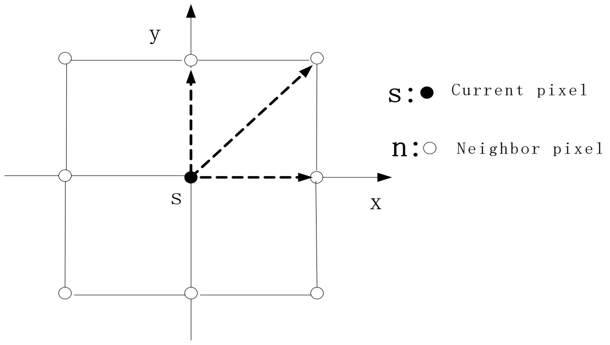


FIGURE 1 New neighbourhood system

3 Unsupervised segmentation of remote sensing image

3.1 PARAMETERS ESTIMATE

Markov Chain Monte Carlo (MCMC) [11] is an easy and effective method for parameter estimation. A number of MCMC algorithms have been reported in related studies; however, the Metropolis-Hasting algorithm is chosen to be used in this study. The posteriori probability $p(\theta_X|X)$ is calculated based on Bayesian theory, where $\theta_X=\{\beta\}$.

$$p(\theta_X|X)=\frac{p(\theta_X)p(X|\theta_X)}{\int p(\theta_X)p(X|\theta_X)d\theta}\propto p(\theta_X)p(X|\theta_X). \tag{8}$$

The Pseudo Likelihood function is introduced to simplify the problem:

$$PL(X|\theta_X)=\ln\prod_{s\in S}p(x_s|\theta_X) \tag{9}$$

and $p(x_s|\theta_X)$ is determined as follows:

$$p(x_s|\theta_X)=\frac{\exp(-U(x_s,\theta_X))}{\sum_{x_s\in G}\exp(-U(x_s,\theta_X))}. \tag{10}$$

The prior probability $p(\theta_X)$ is not considered because the priori information is useless in this application. In the Metropolis-Hasting algorithm, the probability of acceptance $\alpha(\theta_X,\theta_X^t)$ can be represented as:

$$\alpha(\theta_X,\theta_X^t)=\min\left(1,\frac{\exp(PL(X|\theta_X)q(\theta_X^t|\theta_X))}{\exp(PL(X|\theta_X^t))q(\theta_X^t|\theta_X))}\right). \tag{11}$$

Symmetrical proposal distribution is chosen, Equation (11) turns to:

$$\alpha(\theta_X,\theta_X^t)=\min\left(1,\exp(PL(X|\theta_X)-PL(X|\theta_X^t))\right). \tag{12}$$

If the current status is θ_X^t , then the new status is obtained using the Equation (12). In summary, find a θ_X as initialization parameter, set the maximum number of iterations N_g for iterative process that operates on $t=1,\cdots,N_g$. Sample the proposal probability $q(\theta_X^t|\theta_X)$ to obtain the next state θ_X^t , compute the acceptance probability using Equation (12). If θ_X is accepted, then the next state is $\theta_X^{t+1}=\theta_X$; otherwise $\theta_X^{t+1}=\theta_X^t$; continue the iterative calculation until t reaches the maximum number of iterations. In order to ensure a smooth convergence, the class simulated annealing (SA) algorithm is used before the MCMC estimate. Hence, the Equation (12) can be rewritten as:

$$\alpha(\theta_X,\theta_X^t)=\min\left(1,\exp\left(\frac{PL(X|\theta_X)-PL(X|\theta_X^t)}{T_t}\right)\right), \tag{13}$$

where T is the coefficient of temperature, $T_t=\gamma T_{t-1}$, $T_0\gamma^N=1$, and N is the number of the iteration of SA. The Markov chain converges to the optimal point after a certain number of iterations. Finally, choose an appropriate number $M(M\le N_g)$, and select $\theta_X^1,\theta_X^2,\cdots,\theta_X^M$ from the results of MCMC, and approximate them according to:

$$\hat{\theta}_X\approx E(\theta_X|X)=\frac{1}{M}\sum_{t=1}^{M}\theta_X^t. \tag{14}$$

3.2 ALGORITHM OF SEGMENTATION

Supervised estimation methods are widely used in image segmentation; however, these are not applicable to the automated processing. Therefore, the unsupervised technique that requires simultaneous segmentation and estimation is essential and the trending of the future. In this paper, an unsupervised estimation technique is used to simultaneously optimize the parameters and perform the segmentation. As mentioned earlier, the goal is to find the optimal solution $(\hat{X},\hat{\theta}_X,\hat{\theta}_Y)$ through the rule of the MAP, from Equation (1):

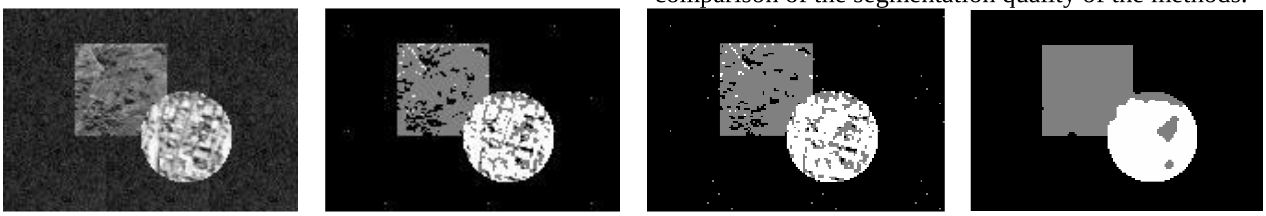
$$\begin{aligned}(\hat{X},\hat{\theta}_X,\hat{\theta}_Y)&=\arg\max_{(X,\theta_X,\theta_Y)}P(Y|X,\theta_Y)P(X|\theta_X)=\\&\arg\max_{(X,\theta_X,\theta_Y)}\ln P(Y|X,\theta_Y)+\ln P(X|\theta_X)\end{aligned}. \tag{15}$$

After taking the logarithm, the optimal solution $(\hat{X},\hat{\theta}_X,\hat{\theta}_Y)$ can be calculated by obtaining maximum of $\ln P(Y|X,\theta_Y)$ and $\ln P(X|\theta_X)$. Using the iterative process described in preceding section $P(Y|X,\theta_Y)$ and $P(X|\theta_X)$ can be obtained under different sets of parameters thus get the maximum of them. However, such a direct maximization is complex and computationally expensive. Therefore, a simplification is performed based on the local optimization standard (POS) proposed by Zhang [12].

Specific algorithm is as follows: firstly, use K-means clustering method or Maximum Likelihood estimation for an initial segmentation and parameters (X',θ'_X,θ'_Y), set 0 to n. Secondly, the initial segmentation result and parameters are substituted into the hidden label field $P(X|\theta_X)$ and observation field $P(Y|X,\theta_Y)$. Then, iteratively calculate the new label results and the parameters estimation using the Equations (3), (4) and (14), it is called hidden label field update and parameters update. Finally, according to the rule of POS, compute $\max(|(\theta'_X,\theta'_Y)-(\theta^*_X,\theta^*_Y)|)\le\varepsilon$ or $n=n_{\max}$; if either of that set up $(\theta^*_X,\theta^*_Y)=(\hat{\theta}_X,\hat{\theta}_Y)$ is the optimal solution; otherwise, assign the parameters to the initial value and continue the step 2 to step 4 until it satisfies the termination condition. Here ε and $n_{\max}$ are the final parameters of the iterative process, calculate them for different kinds of parameters.

5 Experimental results

In order to describe the quality of segmentation quantitatively, the segmentation is performed on an artificial synthesis of remote sensing images using three different methods: K-means clustering, the classical hidden Markov fields (HMF) method, and the proposed unsupervised segmentation algorithm. Figure 2 summarizes the results of three algorithms and presents a comparison of the segmentation quality of the methods.



a) Original image b) K-means clustering c) HMF d) proposed method

FIGURE 2 Synthesis of remote sensing image and results of segmentation

It can be seen from the diagram that K-means clustering and the HMF segmentation methods are sensitive to noise and the distribution of grey value. In contrast, the method we described has a certain inhibitory effect to the noise since the relationship between the pixels in local space is considered. Additionally, it optimizes the result of K-means clustering by significantly improving the regional consistency. The Kappa coefficient, classification error rate, and running time are calculated and presented in Table 1. The larger value of the Kappa coefficient with the lower of classification error rate shows a greater effect on segmentation. The evaluation results are consistent with the human vision system. However, a longer running time is required for the proposed method due to higher complexity compared to the other two methods.

Test the segmentation effect using real SAR images of different scenarios, as shown in Figure 3, where Figures 3a are original SAR images; Figures 3b are segmentation results of K-means clustering; Figures 3c are segmentation results of the classical HMF and Figures 3d are the segmentation results of proposed method in this paper.

TABLE 1 Segmentation quality assessment of different method

Method	**Criteria of segmentation quality assessment**		**Running time(/s)**
	Segmentation error rate	**Kappa coefficient**	
K-means clustering	0.0645	0.8272	0.1803
HMF	0.0247	0.8992	1.6508
Proposed method	0.0155	0.9633	55.5314

It can be seen from the segmentation results (Figures 3d) that different objects such as a river flowing across land or the runway of the airport are clearly segmented without the speckle noise effect. However, some false classification points may exist when the distribution of grey value is complicated. For example, further refinement is needed when there is a series of overlapping pixels overlying both the land and river.

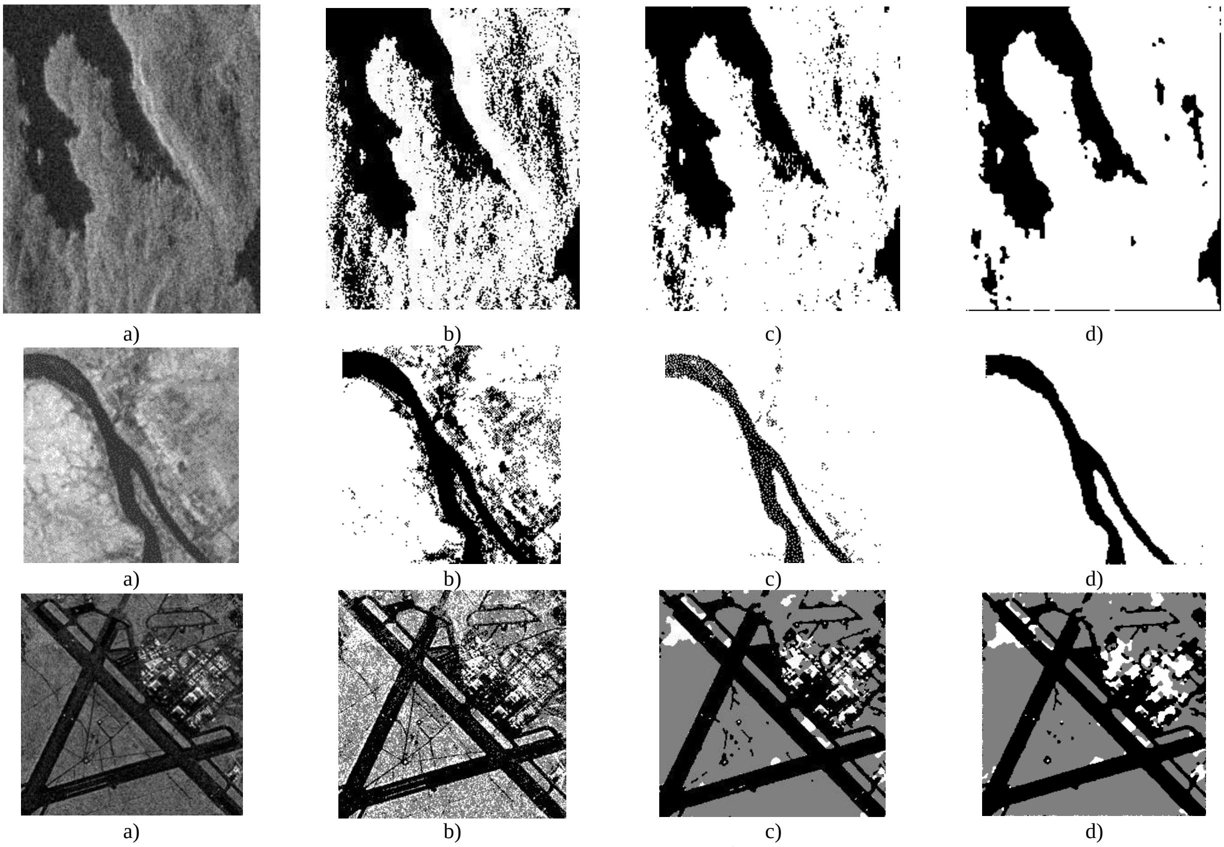


FIGURE 3 Real SAR image and results of segmentation

6 Conclusion

In this paper, a novel neighbourhood system and energy function of MRF model are proposed to improve the accuracy of the image segmentation in remote sensing applications. The proposed method has been applied on SAR image segmentation and the experimental results show that the proposed method can obtain better segmentation effect with the optimized parameters compared to other methods. However, it has a disadvantage of higher complexity resulting in slightly slow processing. It is planned to reduce the complexity of the proposed method in future studies.

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Authors

Jiajing Wang, born in April, 1985, Harbin, Heilongjiang, P.R. China

Current position, grades: the Associate Engineer of No.92677 Unit of PLA, China.
University studies: B.Sc and M.Sc. in Information and Communication Engineering from Harbin Engineering University in China.
Scientific interest: remote sensing image, SAR image processing.
Publications: 3 papers.
Experience: 2 scientific research projects.

Shuhong Jiao, born in 1966, Harbin, Heilongjiang, P.R. China

Current position, grades: Professor at the College, Information and Communication Engineering at Harbin Engineering University, China. Member of Graphic Image groups and biomedical engineering society of Heilongjiang.
University studies: Ph.D in Information and Communication Engineering at Harbin Enginerring University in China.
Scientific interest: image processing, machine vision and precision guidance.
Publications: 40 papers.
Experience: teaching experience of 20years.

Zhenyu Sun, born in August, 1985, Dalian, Liaoning, P.R. China

Current position, grades: Associate Engineer of No.91550 Unit of PLA, China.
University studies: B.Sc in Electrical Engineering at Harbin Engineering University in China.
Scientific interest: remote sensing technology, image processing.
Publications: 3 papers.
Experience: researching applications of remote sensing technology for 5 years. 2 scientific research projects.