USING LOCAL TRANSITION PROBABILITY MODELS IN MARKOV RANDOM FIELD FOR MULTI-TEMPORAL IMAGE CLASSIFICATION

Fu Wei, Guo Ziqi, Zhou Qiang, Liu Caixia, Zhang Baogang*

State Key Laboratory of Remote Sensing Science, jointly sponsored by the Institute of Remote Sensing Applications of Chinese Academy of Sciences and Beijing Normal University
Beijing, 100101, China
*Corresponding author. Email address: fuwei_irsa@yahoo.cn

1. INTRODUCTION

Classification of the remote sensing images is mainly based on the spectral information in pixel level, which often results in the problem of spectral confusion, that is to say the same objects with different spectral and different objects with the same spectral. Meanwhile there are multi-temporal and multi-sensor images and pixels on multi-temporal image show dependencies in both the spatial and temporal domains. So we consider adding spatial and temporal information to improve discriminative power and remove the spectral confusion brought by only considering spectral information on single date image.

The local property of an image shows that the gray value of one pixel only relates to the gray values of its neighborhood and Markov Random Field model can symbolize this local property [1]. Markov Random Fields (MRF) is a commonly used probabilistic model for image analysis, whose basic idea is to model the contextual correlation among image pixels in terms of conditional prior probabilities of individual pixels given their neighboring pixels [2]. As the Gibbs model is equivalent to Markov property of random field, the Gibbs random field model was used to describe the neighborhood random filed [3]. Previous work of image analysis using MRF often focus on the spatial neighborhood modeling, but in classification of the multi-temporal remote sensing images modeling of temporal neighborhood has extended the applied area of MRF.

2. METHODS

2.1. Data Source

The study area is located in the central part of China, and Poyang Lake is the largest fresh lake in China through which water flows to Yangtze River. At the same time it is an important international wetland taking vital part in keeping the ecological variety. Two Beijing-1 images of this area obtained on 7 August 2007 and 1 January 2008 were used in our research.

2.2. Procedure

The process was divided into a few steps. Firstly, the class conditional probability $P(d(i)/c(i))$, which is modeled by a Finite Gaussian Mixture (FGM) distribution of the spectral data d (i), was estimated by the Expectation Maximization (EM) algorithm and this estimation converged to the Maximum likelihood estimation (MLE). Spectral energy function is specified as follows:

$$U_{spectral}(c(i), d(i)) = -\log\left[p(d(i) \mid c(i))\right] \tag{1}$$

The initial classification map using Maximum Likelihood Classification (MLC) was used as the initial classification of the spatial-temporal contextual algorithm in this paper.

Secondly, MRF was used to model the conditional prior probability $P(c_1(i) \mid c_1(N_s(i)), c_2(N_T(i))$, that is to say class prior probabilities of images under the condition of the spatial and temporal neighborhood class label information $c_1(N_s(i)$ and $c_2(N_T(i)$. A Gibbs Random Field (GRF) was used to specify the conditional prior probability by energy function of the class label of the pixel and its neighboring pixels:

$$P(c_1(i) \mid c_1(N_s(i)), c_2(N_T(i)) = U_s(c(i), c(N_s(i))) + U_T(c_1(i), c_2(N_T(i))) \tag{2}$$

Specification of spatial energy function is as follows:

$$U_s(c(i), c(N_s(i))) = \beta_s \sum_{j \in N_s(i)} -I(c(i), c(j)) \tag{3}$$

where β_s is a spatial association parameter; I(c(i),c(j)) is the association factor between class c(i) and class c(j).The temporal energy function was modeled by a transition probability matrix which defines the probability of one pixel belonging to one land cover type at time T_1 given that it belongs to one land cover type at time T_2. Specification of temporal energy function is as follows:

$$U_T(c_1(i), c_2(N_T(i))) = \beta_T \sum_{j \in N_T(i)} -P(c_1(j) \mid c_2(j)) \tag{4}$$

Where β_T is a temporal relation parameter; $P(c_1(j) \mid c_2(j))$ is the temporal transition probability from class $c_2(j)$ to class $c_1(j)$.

To estimate the transition probabilities, it can be specified as a global model by assuming spatial stationarity of the transition probabilities or a local model which is adaptive to the spatial variation of the transition probabilities [4]. In this paper, we divided the whole image into a few sub-images according to the spatial variation and used an iterative EM-like algorithm to estimate the local transition probabilities of each sub-image [5]. Such estimates were initialized by assigning equal probabilities to each pair of classes and the algorithm was iterated until convergence. Model parameters β_s and β_T involved in the spatial and temporal energy functions are crucial to determine the importance of different energy functions and in this paper the two parameters were determined by cross-validation.

Lastly, spectral energy from the EM algorithm and spatial-temporal conditional prior probabilities from MRF were integrated into posterior estimates by Bayes rule, the optimal classification was achieved when the classification corresponds to maximum a posteriori (MAP). The combination of the MAP method with the MRF modeling makes the classification task equivalent to the minimization of a total energy function and the iterative conditional mode (ICM) algorithm, a simple and computationally moderate solution, was used to optimize the MRF–MAP estimates as it converges to a local, but usually good, minimum of the energy function [6].

3. RESULTS

Accuracy assessments were performed for the MLC and spatial-temporal classifications results by using the ground truth data. The results show that the spatial-temporal classification accuracy has been improved compared to non-contextual method. Speckles of classification results are reduced due to spatial smoothing with the incorporation of spatial information. Spectrum confusion between grass and crop and forest in January, 2008 was removed by adding the temporal information in August, 2007 because most grass had disappeared caused by the flush water in August. Accuracy of classification using the local transition probabilities of sub-images incorporated in the temporal information is higher than classification using the global transition probabilities of whole image for both two dates images, showing that local transition probabilities is more accurate than global transition probabilities. The temporal energy parameter is larger than spatial energy parameter in 2008, indicating temporal information is more useful than spatial information due to the accurate temporal information contained in 2007 classified result, and larger temporal weight is found to increase the influence of accurate temporal information.

4. CONCLUSIONS

In conclusion, a spatial-temporal classification algorithm that explicitly integrates spectral, spatial and temporal information in multi-temporal images can achieve significant improvements over non-contextual classification. MRF is an efficient probabilistic model for analysis of spatial and temporal contextual information. The local transition probability in MRF is more accurate than global transition probability, but computationally, the global model is the cheapest and fastest model. And the temporal energy parameter will adjust to different transition probability to make a better MRF model to improve the classification accuracy.

5. REFERENCES

[1] A.H.S. Solberg, T. Taxt, A.K. Jain, "A Markov Random Field Model for Classification of Multi-source Satellite Imagery", IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, 41, pp.100-113, 1996.

[2] D. Liu, M. Kelly, P. Gong, "A spatial–temporal approach to monitoring forest disease spread using multi-temporal high spatial resolution imagery", Remote Sensing of Environment, 101, pp.167-180, 2006.

[3] N, Huang, M.H. Zhu, S.R. Zhang, "A Remotely Sensed Image Classification Algorithm based on Gaussian Hidden Markov Random Field Model", Journal of Electronics and Information Technology, 25, pp.50-53, 2003.

[4] D. Liu, K. Song, J.R.G. Townshend, P. Gong, "Using local transition probability models in Markov random fields for forest change detection", Remote Sensing of Environment, 112, pp.2222-2231, 2008

[5] L Bruzzone, D.F. Prieto, S.B. Serpico, "A Neural-Statistical Approach to Multitemporal and Multisource Remote-Sensing Image Classification", IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, 37, pp.2478-2487, 1999.

[6] F. Melgani, S.B. Serpico, "A Markov Random Field Approach to Spatio-Temporal Contextual Image Classification", IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, 41, pp.2478-2487, 2003.