MARKOV RANDOM FIELD BASED SUPER-RESOLUTION MAPPING FOR IDENTIFICATION OF URBAN TREES IN VHR IMAGES

Juan Pablo Ardila, Valentyn Tolpekin, Wietske Bijker

Phd candidate, Assistant professor, Assistant professor, International Institute for Geo-Information Science and Earth Observation (ITC)

1. INTRODUCTION

Benefits of urban trees range from carbon sequestration, alleviation of the urban heat island effect, savings in energy consumption, appreciation of real estate, to the emotional effect on citizens [1-2]. Municipalities need detailed inventories of urban trees to quantify those benefits, determine the return of investment of forestry practices and to set plans for greener cities. Although remote sensing provides valuable information for vegetation mapping, it is difficult to semi-automatically derive information on urban trees from images due to complexity of the urban space, spectral variability of tree species and limited spectral and spatial resolution of satellite images. The spatial resolution of present spaceborne very high resolution (VHR) sensors still does not permit the generation of individual tree inventories [3], as young trees may have a crown diameter less than 5 m whereas the fine spatial resolution is in the order of 2 m and 0.5 m for multispectral and panchromatic mode respectively.

Hence, a solution is needed to better exploit the information provided by spectral and panchromatic modes of VHR datasets to facilitate identification of urban trees. Image fusion techniques, which synthesize a multispectral image with a finer spatial resolution panchromatic image, may introduce spectral and geometrical distortions [4]. In this study we propose a super-resolution mapping (SRM) method based on Markov random fields (MRF) for identification and delineation of tree crown objects in urban areas by combining the multispectral and panchromatic information of VHR imagery and by modeling the spatial dependence of neighboring image pixels.

2. METHODS

SRM is a novel land cover classification technique which produces a hard classification map of a finer resolution than that of an input multi spectral image. In [5], SRM approaches are divided into two categories: regression or learning algorithms, which include geostatistical models, and spatial optimization algorithms, such as pixel swapping, simulated annealing (SA) and Hopfield neural network. So far SRM has been used mainly in experimental datasets or particular study cases. Some studies can be found on SRM of vegetation [6-7] but so far little has been reported on urban tree inventories.

In [8] an alternative to model spatial dependence in super-resolution maps was described, considering an MRF with SA to produce super resolved maps after initial identification of class fractions at a pixel level. In [9], this has been further explored and evaluated for synthetic images under different class separability conditions. In this study we extend the SRM method of [8-9] to include the fine resolution panchromatic band, usually available in VHR images. We consider the classification of a multispectral remote sensing image y that consists of N_b spectral bands with spatial resolution noted as R with pixel locations $b_j \in B$ where B is a $M_1 \times M_2$ pixel matrix. The panchromatic image is noted as p with finer spatial resolution r, $r < R$. The super-resolution map c is defined on the set of pixels A and covers the same extent on the ground as y and p with spatial resolution r. The scale factor $S=R/r$ is an integer for common VHR images. Hence each pixel b_j corresponds to the area on the ground covered by S^2 finer resolution pixels $a_{j|i}$, $i=1,\ldots,S^2$.

We further assume the existence of a multispectral image x defined on the set of pixels A with N_b multi-spectral bands and fine spatial resolution r. Image x is not observed directly while images y and p are considered as spatial and spectral degraded observations of x respectively. Furthermore, we assume that each pixel in the image x can be assigned to a unique class: $c(a_{j|i})=\alpha$, with $\alpha \in \{\text{tree, background}\}$. The relationship between y and x, and p and x are established by a degradation model as:

$$y_k(b_j) = \frac{1}{S^2}\sum_{i}^{S^2} x_k\left(a_{j|i}\right), k = 1, \ldots, N_b$$

$$p\left(a_{j|i}\right) = \frac{1}{N_b}\sum_{k}^{N_b} x_k\left(a_{j|i}\right)$$

Prior and conditional probabilities are specified by energy functions [10]. Thus, we formulate the prior probability of the SR map c, and the posterior probability to observe the super-resolution map c given y and p as:

$$Pr(c) = \frac{1}{Z_p} exp\left(-\frac{U(c)}{T}\right);\ Pr(c|y) = \frac{1}{Z_t} exp\left(-\frac{U(c|y)}{T}\right);\ Pr(c|p) = \frac{1}{Z} exp\left(-\frac{U(c|p)}{T}\right),$$

respectively. According to the Gibbs equivalence theorem, the SR map c corresponds to the minimum of the posterior energy, which is defined by:

$$U(c|p,y) = \lambda U_c(c) + (1-\lambda) U_{likeli\ hood}(p,y|c),$$

where λ, $0 \leq \lambda \leq 1$, is the smoothness parameter controlling the contribution of prior and likelihood terms in the MRF model. The prior energy $U(c)$ is modeled as the sum of pair-site interactions for a neighboring window W defined as in [9]. For the likelihood model, a parameter λ_{pan} is introduced to control the contribution of the panchromatic and multispectral terms in the model as follows:

$$U_{likeli\ hood}(p,y|c) = \lambda_{pan}\, U_{PAN}(p|c) + \left(1-\lambda_{pan}\right) U_{MS}(y|c),$$

where $0 \leq \lambda_{pan} \leq 1$. We model these energy functions with the normal distributions for the pixels of each class k in the panchromatic and multispectral images p,y. This requires the user to specify the mean and covariance matrix for each class, for example by defining a training set.

3. EXPERIMENTS AND RESULTS

For the study we selected two rectangular areas of a Quickbird image covering a residential area in The Netherlands. These areas comprise groups of urban trees with crown diameters ranging between 3 and 15 m surrounded by impervious surface and vegetation (Figure 1-2 top left). We compared the performance of the SRM classification (Figure 1-2 bottom right) with conventional maximum likelihood classification (MLC) of the 2.4-m multispectral bands (Figure 1-2 bottom left) and of the image obtained by fusing multispectral and panchromatic bands through the High Pass Filter (HPF) method (Figure 1-2 bottom center).

For ML and SRM classifications training areas were selected over the full extent of the Quickbird image for impervious areas, grassland, shadow, and tree crown categories. At least 350 pixels were collected for each class in the panchromatic and multispectral bands and from these mean and covariance matrix were calculated.

The SRM energy function was minimized by simulated annealing with an exponential cooling schedule as in [8]. The initial point for SRM was obtained from the ML classification of the multispectral bands. MRF was implemented in a C++ program and model parameters were optimized on a trial and error basis against user and producer accuracy. We compared per-pixel accuracy of tree identification results with a manually digitized reference image assisted with ground survey (Table 1).

5. CONCLUSIONS

The study shows the use of the multispectral, panchromatic information and spatial optimization via MRF to identify individual urban trees in VHR images. The SRM method produced better results than conventional MLC over both the multispectral and the HPF enhanced image when tested in two areas of a Quickbird image. In future work we intend to validate the model for larger areas, incorporate texture measures in the SRM model and perform object-based accuracy assessment of the SRM results.

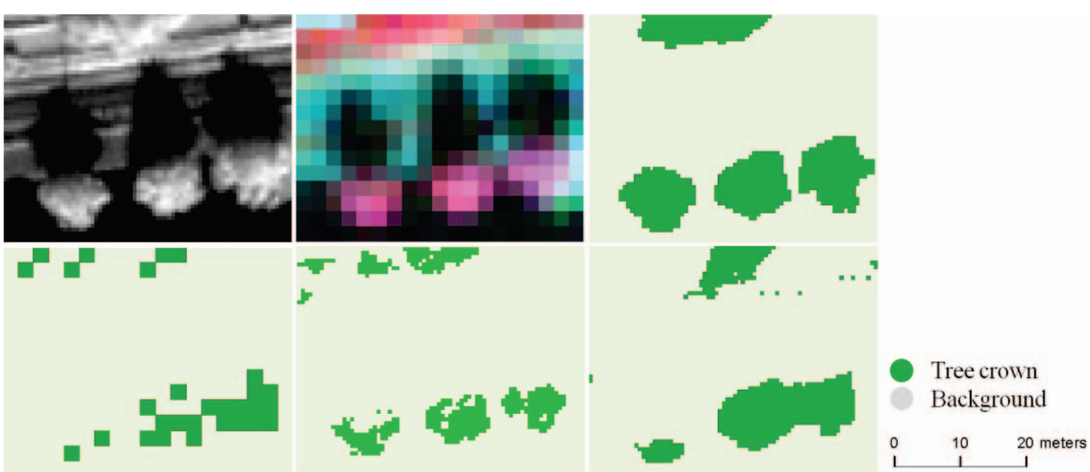

Figure 1. Area 1. Top: (left) Panchromatic band; (center) multispectral bands; (right) reference image; Bottom: (left) MLC multispectral image; (center) MLC HPF image; (right) SRM

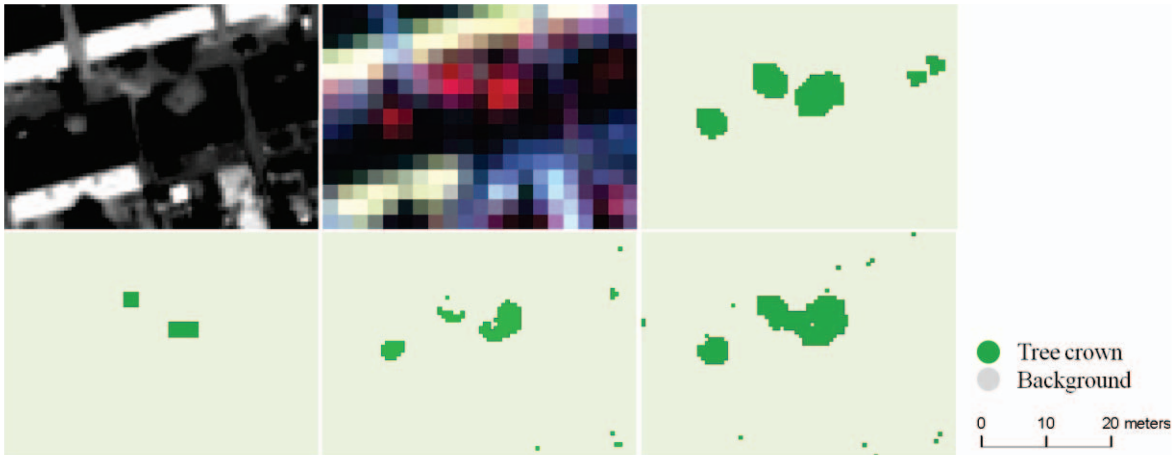

Figure 2. Area 2. Top: (left) Panchromatic band; (center) multispectral bands; (right) reference image; Bottom: (left) MLC multispectral image; (center) MLC HPF image; (right) SRM

Table 1. User and Producer accuracy of tree crown detection in test sites.

	Area 1		Area 2	
	User	Producer	User	Producer
MLC MS	85.2	38.5	97.9	17.2
MLC HPF	93.3	48.3	41.7	18.0
SRM MS+Pan	81.1	57.6	79.9	77.0

6. REFERENCES

[1] E. G. McPherson, D. J. Nowak, and R. A. Rowntree, "Chicago's urban forest ecosystem: results of the Chicago Urban Forest Climate Project " Department of Agriculture, Forest Service, Northeastern Forest Experiment Station, Radnor, PA: U. S.1994.

[2] G. Kuchelmeister and S. Braatz, "Urban forestry revisited," *Unasylva,* vol. 44, 1993.

[3] F. A. Gougeon and D. G. Leckie, "The individual tree crown approach applied to Ikonos images of a coniferous plantation area," *Photogrammetric Engineering and Remote Sensing,* vol. 72, pp. 1287-1297, Nov 2006.

[4] L. Alparone, L. Wald, J. Chanussot, C. Thomas, P. Gamba, and L. M. Bruce, "Comparison of Pansharpening Algorithms: Outcome of the 2006 GRS-S Data-Fusion Contest," *Geoscience and Remote Sensing, IEEE Transactions on,* vol. 45, pp. 3012-3021, 2007.

[5] P. M. Atkinson, "Issues of uncertainty in super-resolution mapping and their implications for the design of an inter-comparison study," *International Journal of Remote Sensing,* vol. 30, pp. 5293-5308, 2009.

[6] M. W. Thornton, P. M. Atkinson, and D. A. Holland, "A linearised pixel-swapping method for mapping rural linear land cover features from fine spatial resolution remotely sensed imagery," *Computers & Geosciences,* vol. 33, pp. 1261-1272, Oct 2007.

[7] A. Boucher, P. C. Kyriakidis, and C. Cronkite-Ratcliff, "Geostatistical solutions for super-resolution land cover mapping," *IEEE Transactions on Geoscience and Remote Sensing,* vol. 46, pp. 272-283, Jan 2008.

[8] T. Kasetkasem, M. K. Arora, and P. K. Varshney, "Super-resolution land cover mapping using a Markov random field based approach," *Remote Sensing of Environment,* vol. 96, pp. 302-314, Jun 30 2005.

[9] V. A. Tolpekin and A. Stein, "Quantification of the Effects of Land-Cover-Class Spectral Separability on the Accuracy of Markov-Random-Field-Based Superresolution Mapping," *IEEE Transactions on Geoscience and Remote Sensing,* vol. 47, pp. 3283-3297, Sep 2009.

[10] S. Z. Li, *Markov random field modeling in image analysis*. New York: Springer, 2009.