TREE CROWN EXTRACTION USING MARKED POINT PROCESSES

Guillaume Perrin, Xavier Descombes and Josiane Zerubia

Ariana Research Group
2004, route des Lucioles, BP 93
06902 Sophia-Antipolis Cedex France
firstname.lastname@inria.fr

ABSTRACT

In this paper we aim at extracting tree crowns from remotely sensed images. Our approach is to consider that these images are some realizations of a marked point process. The first step is to define the geometrical objects that design the trees, and the density of the process.
Then, we use a Reversible Jump MCMC[1] dynamics and a simulated annealing to get the maximum a posteriori estimator of the tree crown distribution on the image. Transitions of the Markov chain are managed by some specific proposition kernels.
Results are shown on aerial images of poplars provided by IFN.

1. INTRODUCTION

The availability of digital aerial photographs of high spatial resolution opens up new prospects for the automatic generation of knowledge in the domain of forestry. Indeed, parameters such as the number of tree crowns, the distribution of the crown diameters or the stem density are currently assessed by human interpretation. Algorithms for the automatic extraction of these parameters would also greatly aid forestry managers in their work.
Extracting tree crowns without information of Digital Elevation Model is a problem which has been widely tackled in the literature over the past few years. Two main directions can be pointed out. The first one considers that tree crown top positions present some radiometric maxima, and performs well for trees located close to the Nadir point of the photograph [2]. It's also possible to delineate the tree crowns if some low grey level valleys separate them [4, 5]. The second one gathers some knowledge-based approaches. For example, adapted ray-traced templates are drawn to detect the tree top positions in [8, 9], and gives good results for trees that are backlighted by the sun.
In this paper, we use marked point processes to extract tree crowns from remotely sensed images. This approach is object-oriented : the points of interest in the process are typically the trees we want to extract. The first issue is also to define a correct geometrical object to design a tree crown. Then, the marked point process is defined by a density which contains both an a priori knowledge on the trees, taking into account the interactions existing between the points in the process, and a data term which fits the objects to the image. This model is sampled by a Reversible Jump MCMC algorithm, coupled with simulated annealing to optimize it thanks to the maximum a posteriori. At each step, the transitions of the Markov chain propose a new state for the current configuration of objects. These transitions are called moves, and are accepted or rejected with a probability depending on both the model and the configurations before and after the transition. One vital aspect of this approach is to model these proposition kernels in order to accelerate the convergence of our algorithm. We test our work on aerial images of stands of poplars, provided by IFN.

2. POINT PROCESSES IN IMAGE PROCESSING

Point processes in image processing have been introduced by Van Lieshout and Baddeley to detect an unknown number of objects [1]. They enable to model complex geometrical objects in a scene with a stochastic framework. They have been widely exploited eversince, and are nowadays used in the extraction of buildings [10] or road networks [7] in remotely sensed images.

2.1 Notations

Let $(U, \mathscr{B}(U), \nu(.))$ be a measurable space, U a subset of some space $\mathbb{R}^d$, and $\nu(.)$ the Lebesgue measure on $\mathbb{R}^d$. A configuration of objects in U will be noted $\mathbf{x}$. Then, we note X a marked point process in U, with positions in P and marks in $K : U = P \times K$. In our application to image processing, P is a subset of $\mathbb{R}^2$, typically $P = [0, X_M] \times [0, Y_M]$ where X_M and Y_M are the dimensions of the image. More details on point processes and their applications can be found in [13].

2.2 A model for tree crown

With the intention of extracting tree crowns from remotely sensed images, the first issue we have to address is the geometrical description of a tree crown, in order to obtain our space U. Several possibilities have been considered on the images given by IFN (see Fig. 1 for an example) : polygonal, elliptical, but the simplest one consists in modeling them by a disc. Also, an object $u \in U$ is thoroughly defined by its position in P and its mark in K, the radius of the disc. This model enables us to work on a small state space $U \subset \mathbb{R}^3$, which will be better for the simulations.

3. DENSITY OF THE PROCESS

As described above, we consider a marked point process X with objects belonging to a state space $U = P \times K$. Each point of this process stands for a tree crown. We note $\mathbb{P}_X(d\mathbf{x})$ its probability distribution, and $h(\mathbf{x})$ its unnormalized density under a dominating measure $\mu_\beta(d\mathbf{x}) = \beta^{n(\mathbf{x})}\mu(d\mathbf{x})$: β is a scaling factor, $n(\mathbf{x})$ the number of objects in $\mathbf{x}$, and $\mu(.)$

The authors would like to thank the French National Forest Inventory (IFN) and Cemagref for providing the data and for interesting discussions. This work has been partly funding by a COLORS grant.

[1] Markov Chain Monte Carlo

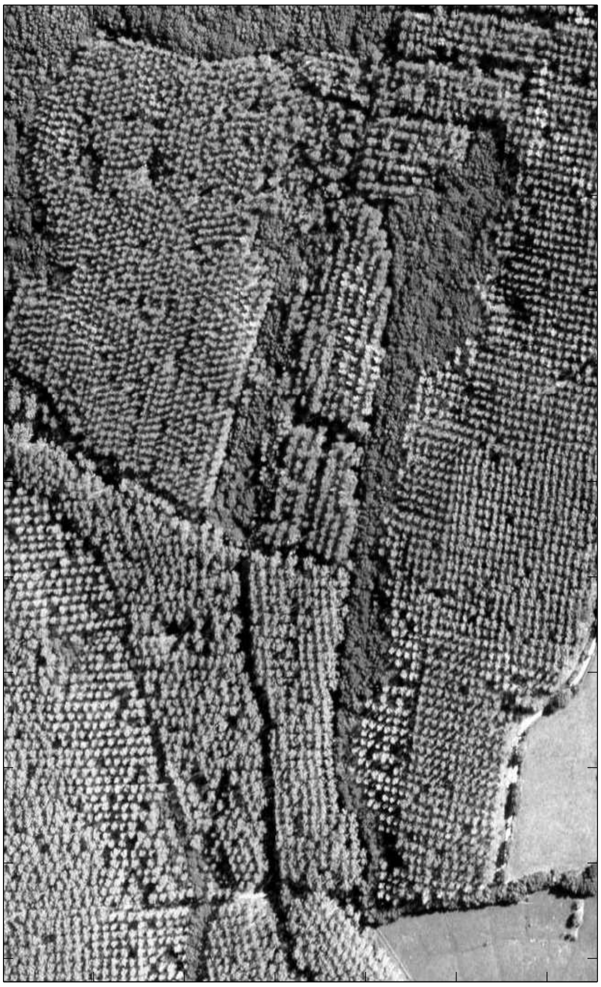

Figure 1: A data image of forest stands in Saône et Loire, France ©IFN.

the distribution of a reference Poisson process with intensity measure $\nu(.)$. This can be written as :

$$\frac{d\mathbb{P}_X}{d\mu_\beta}(\mathbf{x}) = h(\mathbf{x})$$

Our goal is to find the configuration $\mathbf{x}$ that maximizes this density.

3.1 Bayesian framework

Let $\mathscr{I}$ be the image from which we have to extract the tree crowns. $h(\mathbf{x})$ is actually the a posteriori density of a configuration $\mathbf{x}$ of objects, given $\mathscr{I}$. In a Bayesian framework, another expression of this density can be obtained thanks to Bayes's rule :

$$h(\mathbf{x}) = h(\mathbf{x}|\mathscr{I}) \propto h_p(\mathbf{x})\mathscr{L}(\mathscr{I}|\mathbf{x}). \qquad (1)$$

A requirement is also to be able to build both an a priori density $h_p(\mathbf{x})$, which includes all a priori knowledge of the objects and their interactions, and a likelihood $\mathscr{L}(\mathscr{I}|\mathbf{x})$, which measures the probability of the data image $\mathscr{I}$, when a configuration $\mathbf{x}$ is given.

In the following, we will tackle the elaboration of these two terms.

3.2 A priori density $h_p(\mathbf{x})$

All the a priori knowledge we have about the objects to be extracted and their interactions should be integrated in $h_p(\mathbf{x})$. Reminding that we first work on stands of poplars, we know that in most of the cases, our objects won't overlap. Indeed, these stands are managed by people who control the distance between two trees. We also have to penalize configurations containing several overlapping objects detecting one single tree in the image.

However, overlapping objects cannot be totally prohibited (ie hard core process) because they exist in some dense areas. Moreover, we must not penalize them equally (ie Strauss process), because we have to make a distinction between an impossible big overlap, and a possible slight one.

We also decide to design an a priori density $h_p(\mathbf{x})$ that depends on the sum of the overlapping areas of each object in the process :

$$h_p(\mathbf{x}) = e^{-\gamma_a A(\mathbf{x})}\ ,\ \gamma_a > 0\ ,\ A(\mathbf{x}) = \sum_{u\in\mathbf{x}} \lambda\left(\cap_{\mathbf{x}}(u)\right) \qquad (2)$$

where $\lambda(.)$ is the Lebesgue measure on P, and $\cap_{\mathbf{x}}(u)$ the subset of P where the object u overlaps the other objects of the configuration $\mathbf{x}$.

3.3 Likelihood $\mathscr{L}(\mathscr{I}|\mathbf{x})$

$\mathscr{L}(\mathscr{I}|\mathbf{x})$ should express the likelihood of the data image $\mathscr{I}$, given a configuration of objects $\mathbf{x}$. We use a similar likelihood to the one that Rue does in [12] where he detects object in a Bayesian framework, considering two classes in his likelihood defined by the objects' silhouettes. Indeed, since the near infrared component enhances the chlorophyll matter in the image, we can easily distinguish two pixel grey level classes : the **t**ree **c**rown (corresponding to high grey level) and the **b**ackground (see Fig. 2). These two classes can be modeled by a normal distribution of grey level with means (μ_{tc}, μ_b) and variances $(\sigma_{tc}^2, \sigma_b^2)$.

Let $\mathbf{x}$ be a configuration of objects in an image $\mathscr{I}$. A pixel p is said to have been classified in the tree crown class if its center in P belongs to one of the objects of $\mathbf{x}$. Otherwise, this pixel is in the background class. The likelihood $\mathscr{L}(p|\mathbf{x})$ of the classification of p in a class $\phi = \{tc, b\}$ is connected with its grey level value y_p, and can be written as :

$$\mathscr{L}(p|\mathbf{x}) = \frac{1}{\sqrt{2\pi}\sigma_\phi} \exp\left(\frac{-(y_p-\mu_\phi)^2}{2\sigma_\phi^2}\right)$$

Then, the likelihood of the image is the product of every pixel classification likelihood :

$$\mathscr{L}(\mathscr{I}|\mathbf{x}) = \prod_p \mathscr{L}(p|\mathbf{x}) \qquad (3)$$

4. MCMC SIMULATION AND OPTIMIZATION

We now have a marked point process X defined by an unnormalized density $h(\mathbf{x})$ under a reference Poisson marked point process. Monte-Carlo samplers enable us to build a Markov

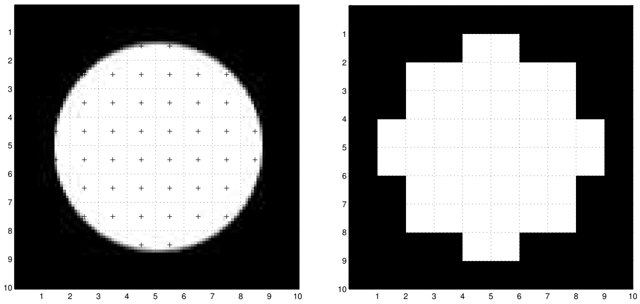

Figure 2: Left : 10×10 image $\mathscr{I}$ and one object of a configuration that let us see the pixel lattice. Right : classification of the pixels, with the **t**ree **c**rown class in white, and the **b**ackground class in black.

Chain (X_k) which converges ergodically to the distribution of X [3]. The transitions of this chain are managed by some proposition kernels, which are moves that we propose to the current configuration. In order to find the configuration maximizing the density, we sample within a simulated annealing scheme, which gives us the Maximum A Posteriori estimator $\mathbf{x}_{MAP}$:

$$\mathbf{x}_{MAP} = arg \max_{\mathbf{x}} (h(\mathbf{x}))$$

To perform simulated annealing, the density $h(\mathbf{x})$ is replaced by a density $h_{T_k}(\mathbf{x}) = h(\mathbf{x})^{\frac{1}{T_k}}$: T_k is the temperature parameter, which decreases geometrically to zero in practice. Since it is not a logarithmic decrease, we are not sure to find the global maximum of the density $h(\mathbf{x})$. The design of the proposition kernels is also essential to insure the exploration of the configuration space.

In [6], Green proposes to add some transformations to the classic birth or death kernel, which is mathematically enough to make the Markov chain visit the whole configuration space, and also to guarantee the convergence of the algorithm. The mixture of kernels we used in our model are uniform birth and death, translation, dilation, combination of translation and dilation, and split and merge (Fig. 3). See [11] for the mathematical details.

This algorithm, called Reversible Jump MCMC (RJMCMC), is described as follows :

At step k, with $X_k = \mathbf{x}_k$:

1. Choose uniformly one of the proposition kernels $Q_i(\mathbf{x}_k, .)$.
2. According to Q_i, propose a new state $\mathbf{y}$.
3. Compute the acceptance ratio of this move, $\alpha_i(\mathbf{x}_k, \mathbf{y})$.
4. With probability $\alpha_i(\mathbf{x}_k, \mathbf{y})$, accept this move : $X_{k+1} = \mathbf{y}$. Otherwise, $X_{k+1} = \mathbf{x}_k$. And so forth.

5. RESULTS

We tested our model on an aerial images of resolution 54 cm/pixel provided by IFN, which represents stands of poplars located in Saône et Loire (France). The trees are close to the Nadir point, and the sun is high. In a near future, our geometrical model will probably have to evolve in order to extract other species, with different kinds of lighting and ground. The result presented on Fig. 4 has been obtained on a 200×140 pixels image (which represents 0.82 ha on the ground), in 212 seconds (1 million iterations) with a SUN - 440 MHz station.

Without the split and merge kernel the extraction is not as good as the one presented here with the same number of iterations, especially in dense areas (see [11]). Indeed, some objects detect several trees, or some trees are extracted by several objects in that case. We do not find the global maximum of the density but only a local maximum. The reason is that we have a too highly correlated Markov chain. The solution would be to decrease more slowly the temperature, but it would take a longer time to converge.

Finally, we can easily access forestry attributes that we need in the final configuration which estimates the maximum of the density $h(\mathbf{x})$.

Statistic	Estimation on Fig. 4
Number of tree crowns	306
Stem density	$374,8$ trees/ha
Mean of the crown diameters	$4.13m$
Variance of the crown diameters	$0.77m$

Table 1: Available forestry attributes.

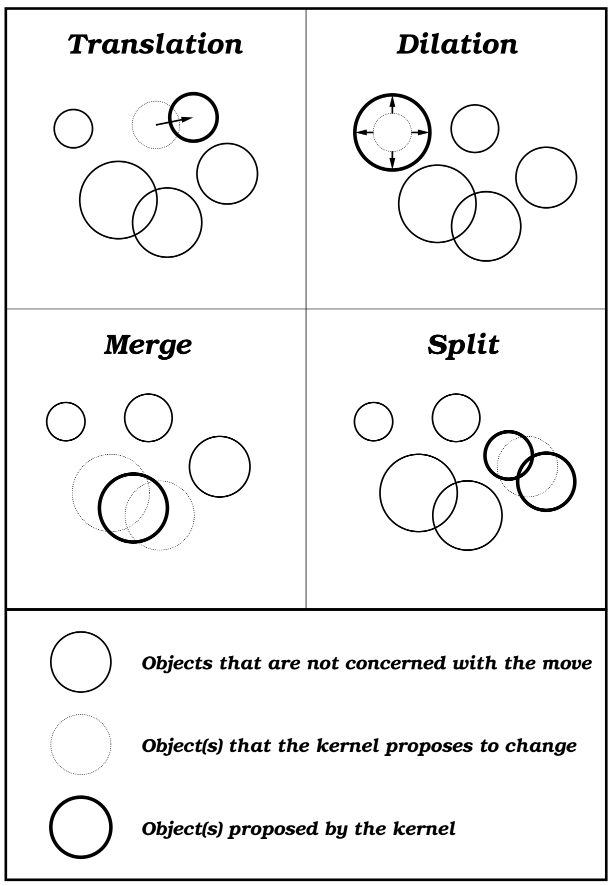

Figure 3: Action of some of the proposition kernels at step k.

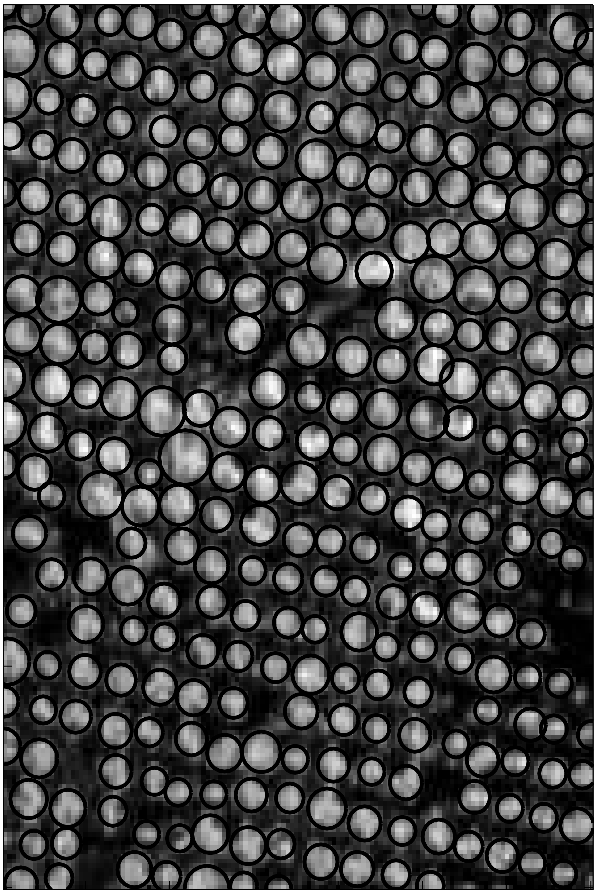

Figure 4: Automatic detection of poplars.

6. CONCLUSIONS

Marked point processes are a new way for automatically extracting tree crowns in forest stands. They enable us to access to important statistics in forestry, such as the number of tree crowns, the stem density, and the diameter of the crowns. The simplicity of the geometrical model presented for poplars is bound to evolve in a near future when we will have to extract other species, with different kinds of lighting and ground. Texture parameters could be useful to model a specific object for each species.

The RJMCMC algorithm that we implemented is well adapted to the simulation and optimization of this process. We noticed that the design of the proposition kernels was essential and had direct consequences on the dynamics : proposing moves in the sampler that are adapted to our application and that accelerate the convergence is essential. Moreover, the Bayesian framework gives us the possibility to automatically estimate the parameters of the model (in particular those of the density).

This approach is quite time consuming, but there are still many ways to improve this point. First, it would be interesting to test different initialisations of the Markov chain (in this work, no object was present in the configuration at time 0) to see what their impact is on the dynamics. For poplars and other stands that present some alignments, Fourier Transform can also give us important knowledge about the objects, which we could inject either in the a priori density or in a new proposition kernel.

REFERENCES

[1] A. Baddeley and M.N.M. Van Lieshout. Stochastic geometry models in high-level vision. In K.V. Mardia, editor, *Statistics and Images*, volume 1, pages 233–258. Abingdon: Carfax, 1993.

[2] K. Dralle and M. Rudemo. Stem number estimation by kernel smoothing of aerial photos. *Canadian Journal of Forest Research*, 26:1228–1236, 1996.

[3] C.J. Geyer and J. Moller. *Stochastic geometry, likelihood and computation*, chapter Likelihood inference for spatial point processes. Chapmann and Hall, Londres, 1998.

[4] F.A. Gougeon. A crown-following approach to the automatic delineation of individual tree crowns in high spatial resolution aerial images. *Canadian Journal of Remote Sensing, 21(3)*, pages 274–284, 1995.

[5] F.A. Gougeon. Automatic individual tree crown delineation using a valley-following algorithm and rule-based system. In D.A. Hill and D.G. Leckie, editors, *Proc. of the International Forum on Automated Interpretation of High Spatial Resolution Digital Imagery for Forestry*, pages 11–23, Victoria, British Columbia, Canada, 10-12 february 1998.

[6] P.J. Green. Reversible jump Markov chain Monte Carlo computation and Bayesian model determination. *Biometrika 82*, pages 711–7320, 1995.

[7] C. Lacoste, X. Descombes, and J. Zerubia. Road network extraction in remote sensing by a Markov object process. In *ICIP*, Barcelona, Spain, september 2003.

[8] M. Larsen. Individual tree top position estimation by template voting. In *Proc. of the Fourth International Airborne Remote Sensing Conference and Exhibition / 21st Canadian Symposium on Remote Sensing*, volume 2, pages 83–90, Ottawa, Ontario, 21-24 june 1999.

[9] M. Larsen and M. Rudemo. Using ray-traced templates to find individual trees in aerial photographs. In Michael Frydrych, Jussi Parkkinen, and Ari Visa, editors, *Proc. of the 10th Scandinavian Conference on Image Analysis*, volume 2, pages 1007–1014, Lappeenranta, Finland, 1997.

[10] M. Ortner, X. Descombes, and J. Zerubia. Automatic 3D land register extraction from altimetric data in dense urban areas. Research Report n^o 4919, INRIA, august 2003.

[11] G. Perrin, X. Descombes, and J. Zerubia. Extraction de houppiers par processus objet. Research Report n^o 5037, INRIA, december 2003.

[12] H. Rue and A.R. Syversveen. Bayesian object recognition with Baddeley's delta loss. *Advances Applied Probability*, 30:64–84, 1998.

[13] M.N.M. van Lieshout. *Markov point processes and their applications*. Imperial College Press, Londres, 2000.