Adaptive Simulated Annealing for Energy Minimization Problem in a Marked Point Process Application

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Abstract. We use marked point processes to detect an unknown number of trees from high resolution aerial images. This is in fact an energy minimization problem, where the energy contains a prior term which takes into account the geometrical properties of the objects, and a data term to match these objects to the image. This stochastic process is simulated via a Reversible Jump Markov Chain Monte Carlo procedure, which embeds a Simulated Annealing scheme to extract the best configuration of objects.

We compare here different cooling schedules of the Simulated Annealing algorithm which could provide some good minimization in a short time. We also study some adaptive proposition kernels.

1 Introduction

We aim at extracting tree crowns from remotely sensed images in order to assess some useful parameters such as the number of trees, their diameter, and the density of the stem. This problem has been widely tackled in the literature over the past years. In the case of color infrared images, some methods use a pixel based approach and give the delineation of the tree crowns [11], other ones use an object based approach by modelling a synthetic tree crown template to find the tree top positions [18].

In [22], we proposed to use a marked point process approach which can embed most of the geometric properties in the distribution of the trees, especially in plantations where we obtained good results. Indeed, marked point processes enable to model complex geometrical objects in a scene and have been exploited for different applications in image processing [6]. The context is stochastic, and our goal is to minimize an energy on the state space of all possible configurations of objects, using some Markov Chain Monte Carlo (MCMC) algorithms

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and Simulated Annealing (SA). In this paper, we will focus on the optimization problem.

The first section is dedicated to recall some definitions about marked point processes. Then, we present our model adapted to tree crown extraction, and the SA algorithm. In the last section, we perform a range of tests in order to study acceleration techniques of the SA that can be used to get good results in a faster way.

2 Definitions and Notations

For more details about marked point processes we refer to [31], and for their applications to image processing to [6].

2.1 Marked Point Process

Let S be a set of interest, called the state space, typically a subset of $\mathbb{R}^n$. A configuration of objects in S is an unordered list of objects :

$$\mathbf{x} = \{x_1, \ldots, x_n\} \in \Psi_n, x_i \in S, i = 1, \ldots, n \tag{1}$$

A point process X in S is a measurable mapping from a probability space $(\Omega, \mathcal{A}, \mathbb{P})$ to configurations of points of S, in other words a random variable whose realizations are random configurations of points. These configurations $\mathbf{x}$ belong to

$$\Psi = \bigcup_n \Psi_n \tag{2}$$

where Ψ_n contains all configurations of a finite number n of points of S.

A marked point process living in $S = \mathcal{P} \times \mathcal{K}$ is a point process where some marks in $\mathcal{K}$ are added to the positions of the points in $\mathcal{P}$. A configuration of objects $\mathbf{x} = \{(p_1, k_1), \ldots, (p_n, k_n)\}$ is also a finite set of marked points. The marks are some parameters that fully describe the object. For example, ellipses are described by the position of their center, their major and minor axis, and their orientation.

The most obvious example of point processes is the homogeneous Poisson process of intensity measure $\nu(.)$, proportional to the Lebesgue measure on S. It induces a complete spatial randomness, given the fact that the positions are uniformly and independently distributed.

2.2 Application to Object Extraction

The marked point process framework has been successfully applied in different image analysis problems [3, 6, 21, 22], the main issue being that we do not know a priori the number of objects to be extracted. The approach consists of modelling an observed image $\mathcal{I}$ (see Fig. (2), lefthandside) as a realization of a marked point process of geometrical objects. The position state space $\mathcal{P}$ will be given by the image size, and the mark state space $\mathcal{K}$ will be some compact set of $\mathbb{R}^d$.