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Forest point processes for the automatic extraction of networks in raster data

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ABSTRACT

In this paper, we propose a new stochastic approach for the automatic detection of network structures in raster data. We represent a network as a set of trees with acyclic planar graphs. We embed this model in the probabilistic framework of spatial point processes and determine the most probable configuration of trees by stochastic sampling. That is, different configurations are constructed randomly by modifying the graph parameters and by adding or removing nodes and edges to/ from the current trees. Each configuration is evaluated based on the probabilities for these changes and an energy function describing the conformity with a predefined model. By using the Reversible jump Markov chain Monte Carlo sampler, an approximation of the global optimum of the energy function is iteratively reached. Although our main target application is the extraction of rivers and tidal channels in digital terrain models, experiments with other types of networks in images show the transferability to further applications. Qualitative and quantitative evaluations demonstrate the competitiveness of our approach with respect to existing algorithms.

1. Introduction

The automatic extraction of networks from images or lidar data is of great interest in various disciplines. For instance, in remote sensing data, roads and rivers represent networks. In medical data, neurons and vessels can be described as network. Knowledge about the appearance of these objects helps to update road maps, to make predictions in case of flood events and to provide information for automated diagnostic systems.

For the automatic extraction of objects, different techniques from the field of image analysis are employed, frequently with the objective to integrate a priori knowledge into the model. The knowledge is often expressed in terms of probabilities and, thus, qualifies probabilistic strategies for object extraction. In image analysis, a well-known approach is the use of *Markov Random Fields* and *Conditional Random Fields* as introduced by Geman and Geman (1984) and Kumar and Hebert (2003). Here, the image is represented by a graph whose nodes correspond to the pixels or segments; the edges indicate local context. Knowledge about the objects in the image may be integrated by favoring similar classes for pixels in a local neighborhood (Li, 1995). However, it is difficult to integrate more global constraints of the objects, e.g. concerning their shape.

In contrast, probabilistic model-based approaches express knowledge about the objects in a more holistic way. While this requires a careful modeling of the objects in order to stay general enough, it allows the integration of object characteristics beyond pixel- or segment-based relations. In this context, the method of spatial point processes has been shown to achieve good results in various disciplines, e.g. for object detection in remote sensing using raster data (Benedek and Martorella, 2014; Chai et al., 2013; Lafarge et al., 2010; Tournaire et al., 2010; Ortner et al., 2007), point clouds (Verdié and Lafarge, 2014; Huang et al., 2013; Descombes and Zerubia, 2002) or for the object detection in terrestrial images (Ge and Collins, 2009; Ripperda and Brenner, 2006).

Such spatial point processes benefit from (1) their flexibility in integrating knowledge about the objects and their relation to other objects, (2) their variability of the number of objects which is not

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restricted in the sampling process, and (3) the determination of a global optimal object configuration.

In this paper, we aim to take advantage of these benefits in order to detect networks in raster data. The paper is structured as follows: First, state-of-the-art approaches dealing with network detection are reviewed (Section 1.1). Then, we describe the mathematical foundation of stochastic optimization with spatial point processes using a Reversible jump Markov chain Monte Carlo sampler coupled with simulated annealing (Section 2). In Section 3, we present the models employed for detecting networks of rivers and tidal channels in digital terrain models (DTMs), but beyond the detection of different types of networks in optical images. Our experimental setting and the results for different data sets are described in Sections 4 and 5, respectively. Finally, conclusions and perspectives for future work are presented in Section 6.

1.1. Related work

Several methods have been developed for the automatic extraction of networks in raster data. In the following, we focus on methods for the detection of (1) rivers and tidal channels - using 3D input data and integrating physical knowledge about the flow direction of water and (2) roads in remote sensing and vessels in medicine - using 2D images and integrating knowledge about the gray values and characteristics of the network.

1.1.1. River extraction

For some hydrological tasks, it is necessary to describe the flow of the water in the whole scene, e.g. in order to enable flood predictions. This is typically done with *flow routing* algorithms using DTMs in the form of raster data as input data, see Gruber and Peckham (2009) and Wilson et al. (2008). Generally, these algorithms calculate the flow of water in the scene which is related to the *catchment area* of each pixel in the DTM. Considering that the movement is mainly driven by gravity and neglecting other influences such as the property of the materials and surface roughness, the flow of the water is only allowed to neighboring pixels with a lower height within these approaches. Two groups of *flow routing* algorithms can be distinguished: (1) *single flow* methods (e.g. *D8* (O'Callaghan and Mark, 1984), *R8* (Fairfield and Leymarie, 1991), *Kinematic Flow* (Lea, 1992)) where the movement is restricted to one neighboring cell and (2) *multiple flow* algorithms (e.g. *TOPMODEL* (Quinn et al., 1991), *FD8* (Freeman, 1991), *MFD* (Holmgren, 1994)) where the flow of the water can be subdivided into multiple neighboring pixels with a lower height. An advantage of these methods is the computational efficiency; some of them are implemented in GIS software packages. However, they focus on steep terrain and are not fully transferable to hydrological applications with nearly horizontal terrain such as tidal channel networks as shown in Lohani and Mason (2001).

The characteristics of tidal channels - structures similar to rivers in Wadden Sea areas - differ from those of normal rivers, because the flow direction changes four times a day due to the tides. As a consequence, specific methods for the automatic detection of these networks have been developed, mainly based on image analysis. For instance, Fagherazzi et al. (1999) consider the height and the curvature of the terrain in DTM at different scales and combine the results in a threshold-based approach. The method detects most of the channels in the input data, but fails for some of the small channels and does not generate a completely connected network. In contrast, Mason et al. (2006) develop an approach starting with low level image processing operations such as edge detectors which are subsequently processed in order to find a channel network. For that purpose, parallel edges corresponding to both channel borders are searched and median axes of the channels are determined and linked based on their directions. The authors also combine the approach with optical input data which, however, does not improve the results (Lohani et al., 2006).

1.1.2. Network extraction with local strategies

A far larger number of network extraction approaches can be found in the field of road detection, see e.g. Mayer et al. (2006), and the diagnosis of networks and trees in medical data such as neurons or blood vessels, see Kirbas and Quek (2004) and Lesage et al. (2009). Here, optical images or 3D image stacks are used as input data.

Some approaches solely consider local characteristics of the network such as geometric and radiometric features in a local neighborhood. These methods benefit from computational efficiency, but have the disadvantage that they are not robust against noise and fail in case of occlusions of the objects in the images. Among this group of approaches, some methods can be characterized as tracking approaches starting from some seed points and directions and expanding the network by iteratively adding points and paths. This is done using a *Kalman filter* strategy by Vosselman and de Knecht (1995) and Movaghati et al. (2010) or by defining statistical tests concerning the width, direction and curvature of roads (Geman and Jedynak, 1996). In (Hu et al., 2007), segments are gradually added to the network by analyzing their shape and deriving the dominant directions of streets. For medical data tracking, Chothani et al. (2011) and Bas and Erdogmus (2011) analyze features based on the Hessian matrix of the gray values in a local neighborhood or the straightness of detected lines in the network. If many streets or vessels are close to each other, a disadvantage of tracking approaches is that the network may be expanded in an incorrect way.

Many approaches define a set of rules for delineating road or vessel networks. Their general strategy is to detect parts of the network starting from an image segmentation (Grote et al., 2012; Gamba et al., 2006; Poullis and You, 2010; Mena and Malpica, 2005) or image classification (Mnih and Hinton, 2010; Marín et al., 2011; Zhang, 2004) and to group these parts based on prior knowledge. In general, the knowledge is integrated in a heuristic way and requires the tuning of a large set of parameters for each scene.

1.1.3. Network extraction with global strategies

In contrast to local methods, global approaches evaluate paths between seed points in the entire input data set and optimize the network for the whole scene. Active parametric contour models (*snakes*) (Kass et al., 1988) first initialize a contour representing the network. This contour is deformed by internal forces (describing knowledge about the smoothness of the contour) and external forces (constraining the network to the data). For road networks the internal and external forces are described by constraints about the linearity and width of streets or about radiometric features in optical images (Gruen and Li, 1995) or SAR data (Bentabet et al., 2003). Wang et al. (2011) also allow the initialized network to expand by adding pixels in a local neighborhood in the case of similar features of these pixels. There are different possibilities to extend the parametrization of the contours, for instance by considering the width of the roads with *Ribbon snakes* (Baumgartner et al., 1999) or modeling the contour by a graph in *network snakes* (Butenuth and Heipke, 2012) and, thus, benefit from the direct consideration of the network topology. However, the modeling by *snakes* requires a good initialization of the network and, thus, makes these methods more suitable to applications where an approximate contour is given or extracted in a preprocessing step.

Another group of global methods is based on minimum cost paths. By using graph structures, the topology is modeled explicitly. For road networks, one of the first approaches using minimum