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Multiple-point geostatistical simulation for post-processing a remotely sensed land cover classification

Yunwei Tang [a,b,*], Peter M. Atkinson [b], Nicola A. Wardrop [b], Jingxiong Zhang [a]

[a] *School of Remote Sensing and Information Engineering, Wuhan University, 129 Luoyu Road, Wuhan 430079, China*

[b] *Geography and Environment, University of Southampton, Highfield, Southampton SO17 1BJ, UK*

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ABSTRACT

A post-processing method for increasing the accuracy of a remote sensing classification was developed and tested based on the theory of multiple-point geostatistics. Training images are used to characterise the joint variability and joint continuity of a target spatial pattern, overcoming the limitations of two-point statistical models. Conditional multiple-point simulation (MPS) was applied to a land cover classification derived from a remotely sensed image. Training data were provided in the form of "hard" (land cover labels), and "soft" constraints (class probability surfaces estimated using soft classification). The MPS post-processing method was compared to two alternatives: traditional spatial filtering (also a post-processing method) and the contextual Markov random field (MRF) classifier. The MPS approach increased the accuracy of classification relative to these alternatives, primarily as a result of increasing the accuracy of classification for curvilinear classes. Key advantages of the MPS approach are that, unlike spatial filtering and the MRF classifier, (i) it incorporates a rich model of spatial correlation in the process of smoothing the spectral classification and (ii) it has the advantage of capturing and utilising class-specific spatial training patterns, for example, classes with curvilinear distributions.

* Corresponding author at: School of Remote Sensing and Information Engineering, Wuhan University, 129 Luoyu Road, Wuhan 430079, China. Tel.: +86 15972925292.

E-mail address: tangyunwei2008@163.com (Y. Tang).

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1. Introduction

Image classification is one of the most important goals in remote sensing, and is used widely to map and monitor changes in land cover on the Earth's surface (Goodchild, 1994; DeFries and Townshend, 1994; Lawrence and Chase, 2010). According to Tobler's first law of geography, everything is related to everything else, but near things are more related than more distant things (Tobler, 1970). For classification problems, the law dictates that more proximate pixels are more likely to belong to the same class. Per-pixel based classifiers, however, do not take spatial context into account, often producing classified maps with salt and pepper noise (Shekhar et al., 2002). Post-processing is often applied to classified images to remove such noise and increase overall accuracy. Commonly, noise is reduced through post-classification smoothing achieved through spatial filtering using a local window. This type of spatial filtering applies an arbitrary spatial weight to all locations, smoothing isolated pixels effectively, but without any model conditioning, so non-model-based filters are insufficient to deal with the full complexity of geographical information.

Besides methods for post-classification processing, algorithms for classifying land cover from remotely sensed imagery have been studied and developed extensively for many years. Classifiers that use spatial information combined with spectral information are known as contextual classifiers (Jensen, 1979; Dutra and Mascarenhas, 1984; Franklin and Peddle, 1990). Many studies have demonstrated that contextual classifiers can achieve greater accuracy than non-contextual classifiers (Magnussen et al., 2004; Park et al., 2003). A sound methodological framework that allows the integration of spatial contextual information in a classification is the Markov random field (MRF) classifier (Solberg et al., 1996; Melgani and Serpico, 2003; Khedama and Belhadj-Aissa, 2004; Thoonen et al., 2012). The *a posteriori* probability of the class is determined by spatial context and usually estimated using an optimisation algorithm. Berthod et al. (1996) compared different optimisation techniques for Bayesian image segmentation using the MRF model. The MRF classifier is described briefly in Appendix A.

Another useful framework for accounting for spatial dependence is geostatistics. Geostatistics is a set of techniques for characterising the interdependence between regional variables and is used widely in many geographical applications. It is based on a Random Field (RF) model parameterised by a variogram or covariance function, and makes predictions of properties of interest at unsampled locations from sparse data (Burrough, 2001). Geostatistical methods have been applied for the purposes of classification. For example: Atkinson and Lewis (2000) presented an introduction to geostatistical classification for remote sensing; and Atkinson (2004) and Atkinson and Naser (2010) integrated a geographical weighting into a per-pixel classifier, resulting in an increase in accuracy. However, reproduction of curvilinear geometries such as river channels and roads calls for the parameterisation of specific shapes or the consideration of the joint categorical variability at three or more points at a time, in preference to two-point statistics such as the variogram (Strebelle, 2002). A method called multiple-point geostatistics was developed to solve this problem.

The initial concept of multiple-point geostatistics was proposed by Guardiano and Srivastava (1993). The idea is to use multiple-point statistics to characterise spatial structures, so that joint variability or joint continuity can be expressed at many more than two locations at a time (Strebelle and Journel, 2001), breaking the traditional limitations caused by the use of two-point statistics. Instead of the variogram, multiple-point geostatistics borrows structures from training images, from which local patterns of the field under study can be captured (Caers, 2001; van den Boogaart, 2006). Guardiano and Srivastava's original implementation of the multiple-point statistical simulation approach builds on the same sequential simulation paradigm as the traditional indicator simulation variogram-based program SISIM (Deutsch and Journel, 1998). It requires the training image to be rescanned each time a new data event is built, which is time-consuming. Strebelle (2000) developed the Single Normal Equation Simulation (SNESIM) algorithm using a "search tree" database to store pre-scanned conditional probabilities followed by sequential simulation. The method estimates the probability directly from a single normal equation equivalent to the identification of a proportion read from the training image. Liu (2006) exemplified the use of the algorithm. Some other methods have been developed to improve SNESIM. For example, direct sampling is a simplified method proposed

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