A new sub-pixel mapping method based on spatial autocorrelation and landscape indexes

Jian Zhang[1]

[1] College of Resources and Environment of Huazhong Agricultural University
Wuhan, 430070, P.R.China
Email:zhangjian_36@126.com;   Mobile Phone:+8613986084638

Geospatial Technology is one of the three emerging technologies in the 21st century. Remote sensing images typically contain a combination of pure and mixed pixels. Mixed pixels result when the sensor's instantaneous field-of-view (IFOV) includes more than one land cover class on the ground. The phenomenon of this "mixed pixels" caused great difficulties to remote sensing image classification. Moreover, it serious impacts on the accuracy and effectiveness of the results of remote sensing image classification. It has become to the major issue which to obstruct the quantitative of remote sensing technology in-depth development.

These mixed pixels pose a difficult problem for RS classification, as their spectral characteristics are not representative of any single land cover class. In fact, the value of each pixel is the composite spectral signature of the land cover types present. For these mixed pixels, fuzzy classifiers can be used, which assign a pixel to several land cover classes in proportion to the area of the pixel that each class covers. Fuzzy techniques aim to estimate the proportions of specific classes that occur within each pixel. The result is a number of fraction images, one for each land cover class concerned. While this information describes the class composition, it does not provide any indication as to how the classes are spatially distributed within the pixel.

A limited number of methods for solving this sub-pixel mapping problem have been proposed. Schneider (1993) introduced a knowledge-based analysis technique for automatic localization of field boundaries in scenes of agricultural areas. It is applicable to homogeneous fields with straight boundaries. Gavin and Jennison (1997) adopted a Bayesian approach and incorporated prior information about the true image in a stochastic model that attaches higher probability to images with shorter total edge length. Atkinson (1997) described an algorithm where the land cover proportions are allocated according to a ranking based on a distance measure, with proximate sub-pixels contributing more than distant ones. Tatem, Lewis, Atkinson, and Nixon (2000) adopted an approach that used the output from a fuzzy classification to constrain a Hopfield neural network formulated as an energy minimization tool. Other techniques make use of additional information in the form of a finer spatial resolution image: Foody (1998) used a regression-based approach, while Gross and Schott (1998) applied constrained nonlinear optimization techniques for image sharpening. Both techniques produce a sharpened fuzzy classification. This paper describes a new approach that formulates the sub-pixel mapping concept as a linear optimization problem maximizing the spatial autocorrelation within the image. It produces a sharpened crisp land cover map, without the need of finer spatial resolution data.

Although the above methods have researched the mixed pixels issue from the aspect of image processing, statistic of the attributes data, etc. The remote sensing imaging mechanism and spatial distribution characteristic of natural landscape had not been considered. This paper describes a new approach that formulates the sub-pixel mapping based on autocorrelation of spatial distribution and shape landscape indexes of the target. This method gets abundance of end-members by mixed-pixel decomposition model, and then the original mixed pixel is divided into smaller units---sub-pixel. Specific sub-pixel mapping algorithm is as follows.

Firstly, assuming the remote sensing image has N_k different types of surface features, and each of them get the abundance of end-members by mixed-pixel decomposition model. And the mixed pixels of the original low-resolution image S_0 have been divided into N^2 sub-pixel. After that the number N_i^{sp} of the sub-pixel of each surface features type can be identified. Based on the spatial autocorrelation of the features distribution theory, the locations of each type feature have been preliminary set on the premise that the number N_i^{sp} of the sub-pixel of each surface features type to be considering.

Secondly, we calculate certain landscape indexes of them according to the shape characteristic of each type of surface. And then the shape and position of the sub-pixel have been adjusted, which in order to close to the real situation. In this paper, some landscape indexes have been used such as fractal dimension index, shape index, linearity index, related circumscribing circle index, etc.

Through the proposed method from this paper, the spatial distribution of end-members of each type features could be get. Thereby the accuracy of remote sensing image classification has been improved and the details of image have been reflected.

Key word: Sub-pixel mapping; Downscaling; Spectral mixture analysis; urban land cover

Abstract:

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