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The effect of the point spread function on sub-pixel mapping

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A B S T R A C T

Sub-pixel mapping (SPM) is a process for predicting spatially the land cover classes within mixed pixels. In existing SPM methods, the effect of point spread function (PSF) has seldom been considered. In this paper, a generic SPM method is developed to consider the PSF effect in SPM and, thereby, to increase prediction accuracy. We first demonstrate that the spectral unmixing predictions (i.e., coarse land cover proportions used as input for SPM) are a convolution of not only sub-pixels within the coarse pixel, but also sub-pixels from neighboring coarse pixels. Based on this finding, a new SPM method based on optimization is developed which recognizes the optimal solution as the one that when convolved with the PSF, is the same as the input coarse land cover proportion. Experimental results on three separate datasets show that the SPM accuracy can be increased by considering the PSF effect.

1. Introduction

Mixed pixels are inevitable in remote sensing images and have brought great challenges in land cover mapping. The spectral unmixing technique has been studied for decades to estimate the proportions of land cover classes within mixed pixels (Bioucas-Dias et al., 2012; Heinz and Chang, 2001; Keshava and Mustard, 2002). The proportions are at the same spatial resolution as the input images and cannot inform the spatial distribution of classes within mixed pixels. To further estimate the spatial distribution of land cover, sub-pixel mapping (SPM) was developed as a post-processing analysis of spectral unmixing outputs. SPM divides mixed pixels to sub-pixels and predicts their class attributes under the coherence constraint from prior spectral unmixing predictions (i.e., coarse land cover class proportions). SPM transforms the conventional pixel-level classification to a finer spatial resolution hard classification (Atkinson, 1997), which can provide more explicit thematic information (e.g., the boundaries between land cover classes can be characterized by more pixels).

In recent decades, various SPM approaches have been developed. As a post-processing step of spectral unmixing, two main groups of SPM approaches can be identified. The first group considers the relation between sub-pixels and solutions are always produced based on defined objectives. Based on the assumption of spatial dependence, the objective can be determined empirically as maximizing the spatial attraction between sub-pixels (Makido and Shortridge, 2007), maximizing the Moran's I (Makido et al., 2007) or minimizing the perimeter of the area for each class (Villa et al., 2011). Based on prior knowledge, the objective can also be matching prior patterns extracted from training images, such as characterized by the semivariogram (Tatem et al., 2002), two-point histogram (Atkinson, 2008) or landscape structure (Lin et al., 2011). The SPM solutions of this type of methods are achieved based on optimization, including the Hopfield neural network (HNN) (Ling et al., 2010; Muad and Foody, 2012; Nguyen et al., 2011; Tatem et al., 2001), pixel swapping algorithm (PSA) (Atkinson, 2005; Shen et al., 2009; Xu and Huang, 2014), maximum a posteriori method (Zhong et al., 2015), genetic algorithm (Li et al., 2015; Mertens et al., 2003; Tong et al., 2016), and particle swarm optimization (PSO) (Wang et al., 2012). Several iterations are involved for this group of SPM methods and, thus, a relatively long computing time may be required. The second group of SPM methods considers the relation between sub-pixels and neighboring pixels. The coarse class proportions within each pixel are used directly to characterize the relation between it and sub-pixels and calculate the fine spatial resolution proportions for sub-pixels. Under the coherence constraint, the sub-pixel classes are determined by comparing the fine spatial resolution proportions. As the coarse proportions are fixed for a given pixel, iterations (as in the first method type) are not necessarily involved and SPM solutions can be produced more quickly. Methods falling into this type include sub-pixel/pixel spatial attraction model (SPSAM) (Mahmood et al., 2013; Mertens et al., 2006; Xu et al., 2014), back-propagation neural network-based algorithm (Gu et al., 2008; Zhang et al., 2008), learning-based algorithm (Zhang et al., 2014), kriging (Verhoeye and Wulf, 2002; Boucher and Kyriakidis, 2006) and radial basis function

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(RBF) (Wang et al., 2014a) interpolation. They can also be summarized as the soft-then-hard SPM (STHSPM) algorithms, a concept proposed in our previous work (Wang et al., 2014b; Chen et al., 2015). In addition, to reduce the uncertainty introduced by spectral unmixing, some SPM methods that do not rely absolutely on coarse proportions were developed, including spatial-spectral methods (Ardila et al., 2011; Kasetkasem et al., 2005; Li et al., 2014; Tolpekin and Stein, 2009), spatial regularization (Ling et al., 2014; Zhang et al., 2015) and contouring methods (Foody and Doan, 2007; Ge et al., 2014; Su et al., 2012).

In remote sensing images, the point spread function (PSF) effect exists ubiquitously. It means that the signal for a given pixel is a weighted combination of contributions from within the pixel and also contributions from neighboring pixels (Townshend et al., 2000; Van der Meer, 2012). The PSF can brighten dark objects and darken bright objects observed from the surface (Huang et al., 2002). It results in a fundamental limit on the amount of information that remote sensing images can contain (Manslow and Nixon, 2002). The PSF is a two-dimensional function accounting for both the across-track and along-track directions (Campagnolo and Montano, 2014; Radoux et al., 2016). The PSF effect is caused mainly by the optics of the instrument, the detector and electronics, atmospheric effects, and image resampling (Huang et al., 2002; Schowengerdt, 1997).

The PSF effect may not be an important issue for homogeneous regions, but it is crucial for heterogeneous landscapes dominated by mixed pixels. To the best of our knowledge, very few SPM methods have considered the PSF effect in downscaling. For example, in most of the existing SPM methods, the coherence constraint from class proportions is satisfied simply by fixing the number of sub-pixels for each class within a single coarse pixel (i.e., the ideal square wave PSF is considered). The number of sub-pixels to be allocated to a class within a coarse pixel is calculated as the product of the coarse class proportion within the coarse pixel and the square of the zoom factor. Due to the PSF effect, however, the coarse proportions estimated by spectral unmixing are actually a function, in part, of the neighboring coarse pixels. The uncertainty in coarse proportions is propagated to the post-SPM process where the coarse proportions contaminated by neighboring coarse pixels are used as the coherence constraint. There is, therefore, a great need for an approach accounting for the PSF effect in SPM to increase the prediction accuracy.

There are two plausible solutions to cope with the PSF effect in SPM. One is to consider the PSF effect in the pre-spectral unmixing process and to estimate more reliable coarse proportions from observed multispectral images. Based on the more reliable predictions, the PSF need not be considered in SPM (i.e., the ideal square wave PSF can be considered in SPM, as in existing SPM approaches). However, spectral unmixing is an ill-posed inverse problem. It is more complicated when part of the neighboring coarse pixels (i.e., neighboring sub-pixels) are involved as this technique is generally performed at the pixel resolution. Currently, it is challenging to account for the PSF in spectral unmixing and obtain reliable proportions. The alternative solution, considered here, is to model the PSF effect in the SPM process, based on the proportions contaminated by neighboring coarse pixels. This strategy is more feasible as SPM is conducted at the sub-pixel scale and contributions from neighboring sub-pixels in PSF can be straightforwardly modeled.

In this paper, to increase the SPM accuracy, the PSF effect is considered directly in the SPM process. Most SPM methods need to first calculate the number of sub-pixels for each class within each coarse pixel. Based on these fixed numbers, the sub-pixel classes are then predicted. This is not a problem for the ideal square wave PSF, as mentioned earlier. When considering the non-ideal PSF, however, the coarse proportions are a convolution of the sub-pixel class values in a larger local window, rather than the single coarse pixel in the ideal square-wave PSF. In this case, the number of sub-pixels for each class in each coarse pixel cannot be determined using only the single coarse proportion (i.e., product of the coarse proportion and the square of the zoom factor, as in existing SPM methods), and it actually cannot be calculated explicitly. In this case, SPM methods such as the STHSPM algorithms are not suitable choices. A plausible solution to this issue is to convolve the fine spatial resolution SPM realization with the PSF and compare the estimated proportion with the actual coarse proportion, and use the error to guide further updating of the current realization. The iteration-based HNN is a method of this type. Therefore, in this paper, the HNN is used to reduce the uncertainty in SPM introduced by the PSF effect.

The remainder of this paper is organized into four sections. Section 2 first introduces the mechanism of the PSF effect in SPM and then the details of the proposed strategy for considering the PSF in SPM. The experimental results for three groups of datasets are provided in Section 3 for validation of the proposed method. Section 4 further discusses the proposed SPM method, followed by a conclusion in Section 5.

2. Methods

2.1. The PSF effect in SPM

This section will illustrate the PSF effect in SPM and demonstrate that the coarse proportions in SPM are a convolution of the sub-pixel class values in a local window centered at the coarse pixel. Let $\mathbf{S}_V$ be the spectrum of coarse pixel V, $\mathbf{R}_k$ be the spectrum of class endmember k ($k = 1, 2, \ldots, K$, where K is the number of land cover classes), and $F_k(V)$ be the proportion of class k in pixel V. Based on the classical linear spectral mixture model (Bioucas-Dias et al., 2012; Heinz and Chang, 2001; Keshava and Mustard, 2002), the spectrum of each coarse pixel is a linear combination of the spectrum of endmembers, where the weights are determined as the class proportions within the coarse pixel. That is

$$\mathbf{S}_V = \sum_{k=1}^{K} \mathbf{R}_k F_k(V) \tag{1}$$

Due to the PSF effect in remote sensing images, Eq. (2) holds

$$\mathbf{S}_V = \mathbf{S}_v * h_V \tag{2}$$

where $\mathbf{S}_v$ is the spectrum of sub-pixel v, h_V is the PSF and $*$ is the convolution operator. For sub-pixel v, its spectrum $\mathbf{S}_v$ can be characterized as

$$\mathbf{S}_v = \sum_{k=1}^{K} \mathbf{R}_k I_k(v) \tag{3}$$

in which $I_k(v)$ is a class indicator as follows

$$I_k(v) = \begin{cases} 1, & \text{if sub-pixel } v \text{ belongs to class } k \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

By substituting Eq. (3) into Eq. (2), we have

$$\mathbf{S}_V = \left[\sum_{k=1}^{K} \mathbf{R}_k I_k(v)\right] * h_V = \sum_{k=1}^{K} \mathbf{R}_k [I_k(v) * h_V] \tag{5}$$

The comparison between Eqs. (1) and (5) leads to

$$F_k(V) = I_k(v) * h_V \tag{6}$$

Let z be the zoom factor, that is, each coarse pixel is divided into z by z sub-pixels. As shown in the one dimensional illustration in Fig. 1, when the PSF takes the ideal square wave filter in Eq. (7)

$$h_V(i,j) = \begin{cases} \frac{1}{z^2}, & \text{if } (i,j) \in V(i,j) \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where (i, j) is the spatial location of the sub-pixel and $V(i,j)$ is the spatial extent of the coarse pixel V containing the sub-pixel at (i, j). Further, the