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Sub-pixel mapping of remote sensing images based on radial basis function interpolation

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ABSTRACT

In this paper, a new sub-pixel mapping (SPM) method based on radial basis function (RBF) interpolation is proposed for land cover mapping at the sub-pixel scale. The proposed method consists of sub-pixel soft class value estimation and subsequent class allocation for each sub-pixel. The sub-pixel soft class values are calculated by RBF interpolation. Taking the coarse proportion images as input, an interpolation model is built for each visited coarse pixel. First, the spatial relations between any sub-pixel within a visited coarse resolution pixel and its surrounding coarse resolution pixels are quantified by the basis function. Second, the coefficients indicating the contributions from neighboring coarse pixels are calculated. Finally, the basis function values are weighted by the coefficients to predict the sub-pixel soft class values. In the class allocation process, according to the class proportions and estimated soft class values, sub-pixels are allocated one of each available class in turn. Three remote sensing images were tested and the new method was compared to bilinear-, bicubic-, sub-pixel/pixel spatial attraction model- and Kriging-based SPM methods. Results show that the proposed RBF interpolation-based SPM is more accurate. Hence the proposed method provides an effective new option for SPM.

1. Introduction

Image classification, one of the most important techniques in remote sensing, is used widely to extract land cover information from remote sensing images. The inevitable mixed pixels (i.e., pixels that contain more than one land cover class) in remote sensing images have brought a great challenge for traditional hard classification-based land cover mapping. To solve this mixed pixel problem, soft classification has been developed to predict land cover proportions for land cover classes that have a spatial frequency higher than the interval between pixels (Bioucas-Dias et al., 2012; Foody, 2000; Heinz and Chang, 2001). Soft classifiers exploit the spectral information of remote sensing images (Wang and Wang, 2013), but fail to predict the spatial location of classes within mixed pixels. To address this issue, sub-pixel mapping (SPM) (Atkinson, 1997) has been developed, in which each mixed pixel is divided into multiple sub-pixels for which class labels are predicted. SPM, thus, transforms a soft classification into a finer resolution hard classification.

SPM is also termed super-resolution mapping (Atkinson, 2009) in the remote sensing literature. It is usually distinguished from super-resolution reconstruction or restitution in the fields of image and signal processing (Atkinson, 2009). For super-resolution reconstruction, the goal is to produce a finer spatial resolution image than that of the input coarse image by superimposing the input coarse image. Further, the output is usually a continuous variable. SPM refers to the prediction of a hard classified land cover map at a finer spatial resolution than the input such that the outputs is a set of categories (class labels). However, there are links between SPM and super-resolution reconstruction: for example, after super-resolution reconstruction of a remote sensing image in units of reflectance, the finer spatial resolution image could then be classified by a hard classifier to achieve SPM (Li et al., 2009).

SPM is often performed based on maximizing spatial dependence with the assumption that the land cover is spatially dependent both within and between pixels. Over the past decades, SPM has gained increasing attention in remote sensing and various SPM algorithms have been developed. As the post-processing of a soft classification, some SPM algorithms involve iterative optimization. Specifically, a fine spatial resolution land cover map is initialized first. Guided by a certain objective with the constraint from

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class proportions (i.e., outputs of soft classification), the initialized fine spatial resolution map is optimized to obtain the SPM result (Atkinson, 2005; Mertens et al., 2003; Makido et al., 2007; Villa et al., 2011; Wang et al., 2012). The optimization process requires several iterations to approach a satisfactory result and often artificial intelligence algorithms are applied to solve the relevant models, such as genetic algorithms (Mertens et al., 2003), simulating annealing (Makido et al., 2007; Villa et al., 2011), Hopfield neural network (Tatem et al., 2001; Muad and Foody, 2012a; Nguyen et al., 2005) and particle swarm optimization (Wang et al., 2012). Much time is always needed in the optimization process.

Another type of SPM algorithm, namely, the soft-then-hard SPM (STHSPM) algorithm (Wang et al., 2014a), involves two steps: sub-pixel sharpening and class allocation. Sub-pixel sharpening is undertaken to obtain the soft class value (between 0 and 1) for sub-pixels while class allocation is used to allocate hard class labels (0 or 1) for sub-pixels according to the estimated soft class values and constraints from the class proportions. Commonly used STHSPM algorithms include sub-pixel/pixel spatial attraction model (SPSAM) (Mertens et al., 2006), back-propagation neural network (Nigussie et al., 2011), Kriging (Verhoeye and Wulf, 2002) and Indicator CoKriging (Boucher and Kyriakidis, 2006; Jin et al., 2012; Wang et al., 2014b).

SPM can also be performed by one-stage methods that instead of taking a soft classified image as input (i.e., two stages of soft classifier and SPM), take the raw image in units of reflectance as input (Kasetkasem et al., 2005; Tolpekin and Stein, 2009; Ardila et al., 2011; Ling et al., 2012a) (thus, one stage). In these methods, spectral and spatial information are considered simultaneously. In addition, Foody et al. (2005) and Su et al. (2012) present a contouring method for SPM that draws the boundaries of classes running through the coarse pixels. This method is more suitable for large objects.

For the STHSPM algorithm, a solution can be achieved without iterations. Note the iterations in the training process in a back-propagation neural network are not considered, since the training process is always off-line. Hence, SPM can be realized quickly for the STHSPM algorithm. Thus, the objective of this paper was to develop further this type of algorithm.

The outputs of sub-pixel sharpening in the STHSPM algorithm are continuous values between 0 and 1, which indicate the probabilities of class occurrence at each sub-pixel. Actually, the task of sub-pixel sharpening can be viewed as downscaling the coarse spatial resolution proportion images to the target spatial resolution. This task can also be accomplished by super-resolution reconstruction when the proportion images are taken as input. It would be worth employing super-resolution reconstruction algorithms for the purpose of sub-pixel sharpening.

In this paper, for the first time, a SPM algorithm based on radial basis function (RBF) interpolation is proposed. Interpolation-based super-resolution algorithms have been used widely for image downscaling. They can process a single coarse spatial resolution image by exploiting the spatial information encapsulated in the input image. As a powerful tool for modeling a non-linear function from given input–output data, RBFs have attracted considerable attention in many areas, such as neural networks (González et al., 2003), solution of differential equations (Pollandt, 1997), scattered data interpolation (Torres and Barba, 2009), and structure optimization (Wang et al., 2007). A detailed overview of RBFs and their applications can be found in Buhmann (2003). RBFs are known widely as a versatile tool for image interpolation (Lee and Yoon, 2010; Magoules et al., 2007). In RBF-based image interpolation, a system of equations is solved to obtain the RBF coefficients that characterize the input–output mapping (Fuji et al., 2012). The matrices described by the basis function are always uniquely solvable for most stencils in two-dimensional space (Lee and Yoon, 2010). RBF interpolation has been shown to be a highly accurate super-resolution reconstruction algorithm (Lee and Yoon, 2010; Magoules et al., 2007), both theoretically and practically, and has gained a wide range of successful applications, including medical image processing (Carr et al., 1997) and computer graphics (Carr et al., 2001). These properties and advantages of RBFs allow their application in SPM. In the proposed RBF interpolation-based SPM, the coarse proportion images are used as input and soft class values at sub-pixels are estimated by RBF interpolation. Conditional upon the original class proportions constraint that fixes the number of sub-pixels allocated to each class per pixel, the estimated soft class values are then hardened to generate a hard classified land cover map at the sub-pixel scale.

The proposed RBF interpolation-based SPM belongs to the aforementioned STHSPM algorithm. Similar to SPSAM-, back-propagation neural network-, Kriging- and Indicator CoKriging-based SPM, the proposed algorithm is a non-iterative method, and the uncertainty introduced by random initialization and stochastic processes involved in the iterations of the first type of SPM can also be avoided. On the other hand, compared to back-propagation neural network- and Indicator CoKriging-based SPM, the proposed SPM algorithm has the advantage of not relying on any prior model of land cover spatial structure. The RBF interpolation-based SPM is performed by exploiting fully the spatial information in the input proportion images.

The remainder of this paper is organized as follows. Section 2 describes the SPM problem. Section 3 gives details of the proposed SPM method, including sub-pixel soft class value prediction and hard class allocation. Experimental results are provided in Section 4 and discussed in detail in Section 5. The conclusions are drawn in Section 6.

2. The SPM problem

The SPM approach in this paper represents a post-processing step following soft classification. In SPM, each mixed pixel is divided into multiple sub-pixels and then their class labels are predicted. The coarse proportion data and the zoom factor are used to calculate the number of sub-pixels for each class. The details are given below.

2.1. Calculation of the number of sub-pixels for each class

Suppose S is the zoom factor (i.e., each coarse pixel is divided into $S \times S$ sub-pixels), P_j ($j = 1, 2, \ldots, M$, M is the number of pixels in the coarse image) is a coarse pixel and $F_k(P_j)$ is the coarse proportion of the k-th ($k = 1, 2, \ldots, K$, K is the number of classes) class for pixel P_j. Considering the physical meaning, the coarse proportions estimated by soft classification (e.g., spectral unmixing (Bioucas-Dias et al., 2012)) usually meet the abundance sum-to-one constraint and the abundance non-negativity constraint, i.e.,

$$\begin{aligned} &\sum_{k=1}^{K} F_k(P_j) = 1, \quad j = 1, 2, \ldots, M \\ &F_k(P_j) \geqslant 0, \quad k = 1, 2, \ldots, K; \quad j = 1, 2, \ldots, M \end{aligned} \tag{1}$$

For a particular pixel, say P_j, the number of sub-pixels for the k-th class, $E_k(P_j)$, is calculated by

$$E_k(P_j) = \mathrm{round}(F_k(P_j)S^2) \tag{2}$$

where round $(\cdot)$ is a function that takes the integer nearest to $\cdot$. The sum of the numbers of sub-pixels for all K classes are S^2.